ADAPTIVE, COMMUNICATION-FREE CHARGE CONTROLLER OF ELECTRIC VEHICLES UNDER DISTRIBUTION NETWORK CONSTRAINTS

BY

SAIFULLAH SHAFIQ

A Thesis Presented to the
DEANSHIP OF GRADUATE STUDIES

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

In

ELECTRICAL ENGINEERING

DECEMBER 2017

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN- 31261, SAUDI ARABIA

DEANSHIP OF GRADUATE STUDIES

This thesis, written by **SAIFULLAH SHAFIQ** under the direction of his thesis advisor and approved by his thesis committee, has been presented and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN ELECTRICAL ENGINEERING.**

Ali Al-Awami

Dr. Ali Taleb Al-Awami
(Advisor)

Dr. Ali Ahmad Al-Shaikhi
Department Chairman

Dr. Mohammad Ali Abido
(Member)

Dr. Salam A. Zummo
Dean of Graduate Studies

عمادة الدراسات العليا
DEANSHIP OF GRADUATE STUDIES

Dr. Muhammad Khalid
(Member)

13/5/18
Date

This thesis is dedicated to my parents and siblings whose continuous support paved my way to achieve this milestone

ACKNOWLEDGMENTS

All the praises and thanks be to Allah, Subhanahu-Wa-Ta'ala, the most Beneficent and most Merciful, who gave me the opportunity to pursue the MS degree at King Fahd University of Petroleum and Minerals. I bow my head before Him for His Grace and Kindness in allowing me this opportunity and sustaining me throughout the experience.

With deepest regard, I would like to thank my family for their unfailing support and continuous encouragement throughout my degree period. I will always be obliged to them for their constant moral support and ever-needed prayers. I would like to acknowledge the continuous support provided by Dr. Ali T. Al-Awami throughout my stay at King Fahd University of Petroleum and Minerals. He was always being there to help me out otherwise I would not have been able to carry out this cutting-edge research. I would also like to acknowledge my thesis committee members Dr. Mohammad Ali Abido and Dr. Muhammad Khalid for their indispensable comments, suggestions, and the time they spent reviewing my thesis report. I would like to express my deepest gratitude to all my friends (especially Mr. Syed Asim Ghalib and Mr. Farhan Ammar Ahmad) at King Fahd University of Petroleum and Minerals for providing me moral support, pleasant atmosphere, and unforgettable moments.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS

$\boldsymbol{\theta}$	:	Voltage Angle
$\boldsymbol{v}$	:	Voltage Magnitude
$\boldsymbol{p}$	:	Total Real Power
$\boldsymbol{q}$	:	Total Reactive Power
$\boldsymbol{J}$	:	Jacobian Matrix
$\boldsymbol{\mu}$	:	Voltage-to-load Sensitivity
$\boldsymbol{\alpha}$	:	Minimum Charging Rate
$\boldsymbol{\beta}$	:	Controller Parameter
$\boldsymbol{v_r}$	:	Reference Voltage
$\boldsymbol{\lambda}$	:	State-of-charge
$\boldsymbol{\bar{P}}$	:	Maximum Charging Rate
$\boldsymbol{EP}$	:	Expected Charging Rate
$\boldsymbol{P}$	:	Actual Charging Rate
$\boldsymbol{\gamma}$	:	Proportional Gain

LIST OF ABBREVIATIONS

DG	:	Distributed Generator
DPL	:	DIgSILENT Programming Language
EV	:	Electric Vehicle
GHG	:	Greenhouse Gases
IC	:	Internal Combustion
OLTC	:	Online-tap Changing
POC	:	Point of Charging
PHEV	:	Plug-in Hybrid Electric Vehicle
SOC	:	State-of-charge
SVC	:	Static Var Compensator

ABSTRACT

Full Name : Saifullah Shafiq

Thesis Title : Adaptive, Communication-free Charge Controller of Electric Vehicles Under Distribution Network Constraints

Major Field : Electrical Engineering

Date of Degree : December 2017

Now-a-days, electric vehicles (EVs) are becoming ubiquitous and their widespread integration in the distribution systems has been a prime area of interest. The downsides of largescale integration of EVs in the power grid outrival their positive aspects unless proper charging strategy is formulated. In this thesis, an autonomous EV charge controller is designed by introducing a novel idea of voltage-to-load sensitivity. The voltage and sensitivity parameters are used as input signals to EV charge controller to adjust the charging rate. The reason behind using the voltage and sensitivity lies in a fact that the node having good voltage is less sensitive to change in load than a node having lower voltage. These complementary characteristics are incorporated to ensure the fairness among EVs charging at different locations in the power system. In addition, state-of-charge (SOC) of EV battery is augmented to enhance the overall efficiency of the proposed charge controller. A three-phase unbalanced test distribution system having eighty-five load buses is used to assess the performance of EV charge controller. The test distribution system employing proposed EV charge control scheme is built and simulated in DIgSILENT PowerFactory environment. Moreover, the robustness of charge controller is validated considering different loading conditions, system reconfiguration, distributed generators (DG), and voltage control devices, such as shunt capacitors and online-tap changing

(OLTC) transformers. Simulation results show that the proposed control structure effectively prevents voltage violations in the system while ensuring fairness among the EVs irrespective of their charging locations in the distribution power system.

ملخص الرسالة

الاسم الكامل: سيف الله شفيق

عنوان الرسالة: تصميم متحكم شحن متكيف دون الحاجه الى الاتصالات مع الاخذ بالأعتبار قيود شبكه التوزيع

التخصص: الهندسة الكهربائية

تاريخ الدرجة العلمية: ديسمبر ٢٠١٧

في هذه الأيام, نجد ان المركبات الكهربائية (EVs) اصبحت واسعة الانتشار بشكل ملحوظ, و اصبحت محط اهتمام كثير من الناس. سلبيات ادخال المركبات الكهربيه بشكل كبير في الشبكه الكهربيه قد تطغى على ايجابياتها, الا لو كان هناك نظام شحن مناسب تم استعماله. في هذا البحث, تم تصميم شاحن مركبات ذو تحكم ذاتي autonomous EV charge controller , عن طريق اضافة فكره جديده مبنيه على فكرة حساسية الفولتيه للحمل الكهربي voltage-to-load sensitivity. الفولتيه و الحساسيه تم استعمالهما كمدخلات لمتحكم الشحن للمركبه الكهربيه بهدف ضبط معدل الشحن في المركبه. و السبب في استعمال الفولتيه و الحساسيه هو ان العقده node التي لديها الفوليه الافضل, لديها حساسيه اقل للتغيرات التي تحدث في الحموله الكهربيه مقارنة بالعقده التي لها فولتيه اقل. هذه الخاصيه يمكن ان تدمج لضمان الانصاف fairness في شحن المركبات الكهربيه في مواقع مختلفه في الشبكه. بالاضافه الى ذلك, حالة الشحن لبطارية المركبه الكهربيه state-of-charge (SOC) تمت اضافتها لتحسين كفاءة متحكم الشحن المقترح. نظام التوزيع غير المتزن ثلاثي الاطوار three-phase unbalanced test distribution system و الذي يحوي خمسه و ثمانين بسبارات حموله load buses , تم استعماله لتقييم اداء المتحكم المقترح. تمت محاكاة و تمثيل المتحكم في برنامج DIgSILENT PowerFactory. متانة المتحكم المقترح تم اختبارها اخذين بعين الاعتبار حالات حموله مختلفه, تركيبه النظام, المولدات الموزعه distributed generators و اجهزة التحكم في الفولتيه, مثل المكثفات المتوازيهshunt capacitors و المولدات ذات نسبه الف المتغيره online-tap changing (OLTC) transformers. نتائج المحاكاه اثبتت فاعلية المتحكم المقترح لثبيت قيمة الفولتيه و كذالك ضمان الانصاف في الشحن بين المركبات الكهربيه.

CHAPTER 1

INTRODUCTION

Conventional transportation technologies have been predominantly accumulating the detrimental effects caused by burning of fossil fuels. Moreover, environmental targets set by governments around the globe, escalating demand for fuel frugality, and higher well-to-wheel efficiency requirements stimulate the demand for efficient and eco-friendly vehicles. Consequently, in a paradigm transition to nature-friendly and sustainable transportation, electric vehicles (EVs) have been widely accepted as a promising alternative that can replace large amounts of conventional vehicles [1].

1.1 Background

EV is defined as any vehicle that employs electric motor for traction, and obtains the driving energy by utilizing energy storage system. The history of EVs includes three main phases. During the first phase, till the beginning of 1900s, steam engines, electric motors and internal combustion (IC) engines had almost similar popularity. Steam engines based vehicles were expensive, dirty, and hazardous whereas EVs were considered better irrespective of their short distance ranges because long trips were uncommon due to limited paved routes [2]. At that time, IC engines based automobiles had recently been developed and it had been the topic of great interest. Moreover, immense expansion of roadways, growing trend of fuel stations, and significant reduction in cost paved the way of IC automobiles to be most attractive solution for years [3],[4].

In the second phase, EVs emergence was catalyzed by the development in the field of power electronics. In 1960s, motor control for EVs remained the prime area of interest especially for the automotive industry [5]. Moreover, it was reinforced due to the oil crisis in 1970s and, as a result, prototypes of EVs were developed. However, the higher cost associated with low energy density batteries as compared to IC automobiles prevented the EVs adoption [6].

Now-a-days, EVs are once again emerging rapidly and becoming popular. The growing trend of EVs in transportation sector is impelled by various factors such as greenhouse gases emissions (GHG), global warming, depleting fossil fuels reserves, and their erratic prices. Moreover, the use of IC vehicles poses serious threats to mankind. Consequently, the European Commission is intended to get rid of conventional vehicles by 2050 [7]. EVs outperform conventional IC vehicles in terms of economic and social aspects. Therefore, many manufacturers currently have one or more EVs in their portfolio. For instance, Tesla has Model S, Model X, and Model 3, BMW has i3, Chevrolet has Bolt EV and Spark EV, Nissan has Leaf, Kia has Soul EV, etc.

1.2 Thesis Motivation

Since the EVs have been accepted as a potential candidate to supersede the conventional vehicles, many manufacturers have already started EV production to grab a significant share of automobiles market in near future. It has been predicted that the US will have three million EVs by 2020 [8]. Now-a-days, a concept of supercharging stations and quick battery swap services are very attractive. Nevertheless, charging EVs at home is also quite promising since EV users can start charging their EVs after they arrive home. However, the existing distribution power system tends to be significantly impacted due to the installment of distributed EV charging stations at homes [9]. An EV load could be as large as, or even larger than, the load of a typical house, and installing an EV charger at home for an individual user can easily be managed by installing a high-power rating outlet. However, simultaneous large-scale EVs charging would significantly increase the load in the distribution power system which may result in overloading of existing transformers [10]-[12], especially those transformers whose installed capacities have been designed without considering the EVs charging load [13]. Moreover, an ample increase in current flowing through distribution feeders due to EVs charging load may result in significant voltage drops, excessive line losses, and sharp peak demands. The impact becomes even worse in the case of long feeders [14]. However, the abovementioned issues can be remarkably alleviated by incorporating EV charging control strategies [12].

Different charging techniques, these can be categorized into centralized, decentralized, and autonomous charging strategies, have been explored and implemented to mitigate the aforementioned problems. Among these charging schemes, autonomous charging approach is the simplest and, arguably, the most reliable technique since it does not require any kind of communication infrastructure. Therefore, this thesis is motivated to design a communication-free charge controller of EVs to eradicate the deteriorating effects of increased penetration level of EVs into the distribution grid. The proposed controller does not require any communication infrastructure since it is based on voltage and voltage-to-load sensitivity parameters.

1.3 Thesis Objectives

The purpose of this thesis was to design communication-free EV charge controller in order to mitigate the impacts caused by EVs charging load on distribution power system considering distribution network constraints. The function of an EV charge controller was to throttle the charging rate of the EV based on the input parameters. The research objectives of this study were:

1. To design a communication-free EV charge controller considering distribution systems considerations, i.e., system reconfiguration and light and heavy loading conditions.

2. To incorporate nodal voltage, nodal sensitivity of distribution system, and state-of-charge (SOC) of an EV in the proposed approach to ensure the fairness among all the EVs.

3. To analyze the effects caused by different EV penetration levels on secondary distribution power system with and without employing proposed charge controller.

4. To study the impact of the proposed controller in the presence of distributed generators (DGs) and voltage control devices such as shunt capacitor and tap changing transformer.

5. To compare the proposed controller with the existing state-of-the-art controller.

1.4 Thesis Methodology

The following methodology was adopted to conduct this research:

Task 1: Recent advancements and literature survey

- Analyzing the recent advancements in development of EVs charging control.

- Reviewing existing control techniques to mitigate the downsides of large-scale EVs integration especially in the distribution power system.

Task 2: Developing and testing on DIgSILENT PowerFactory

- Developing distribution power system in DIgSILENT PowerFactory software.
- Writing codes to learn basics of DIgSILENT Programming Language (DPL).

Task 3: Designing charge controller for EVs

- Writing codes to measure nodal voltage, calculate sensitivity, and update load.
- Designing EV charge controller based on nodal voltage, sensitivity, and SOC.

Task 4: Reconfiguring the test distribution system

- Testing the proposed controller considering light and heavy loading conditions.
- Analyzing the proposed EV charge controller by changing network topology.

Task 5: Incorporating DG unit and other devices

- Including DG units to assess the effectiveness of the proposed methodology.
- Integrating shunt capacitor and on-load tap changing transformer in a system.

Task 6: Investigating the efficacy of proposed controller

- Evaluating the usefulness of proposed approach under various operating states.
- Comparing the proposed controller with benchmark controllers.

1.5 Thesis Structure

The thesis is structured as follows: Chapter 2 covers the literature review about different charging techniques of EV charge controllers, such as, centralized, decentralized, and autonomous charging techniques. It also covers different methods of measuring the voltage-to-load sensitivity. Chapter 3 describes the proposed autonomous EV charge controller. It also explains the concept of online measuring sensitivity to load changes. Chapter 4 provides the information and data of the test distribution power system as well as the EVs (i.e., Nissan Leaf Model SV and Tesla Model S) which are considered in this research. In Chapter 5, results are discussed in detail with tables and figures showing the effectiveness of the proposed controller. The conclusion and future works are presented in Chapter 6.

CHAPTER 2

LITERATURE REVIEW

The rising concerns of greenhouse gases (GHG) emissions, global climatic interests, scarcity of fossil fuels reserves, and their volatile prices impel the automobile industry to utilize sustainable and environmental friendly resources. The transportation sector contributes 23% of the world CO_2 emissions [15]. Due to these reasons, the target of 130 g CO_2/km was set by European Commission for 2015 which has been reduced to 95 g CO_2/km for 2021 [16]. Similarly, new fuel economy standards were announced by US government in 2012. According to these standards, passenger cars and light duty trucks should have the average fuel economy of 4.3 liter/100 km by 2025 [17]. Moreover, similar policies have also been introduced in China and Japan [18]. These targets cannot be realized solely by improving the efficiency of conventional vehicles. However, the electrification of transportation sector can catalyze the process of achieving these aggressive targets set by different governments around the globe.

The conventional transportation sector has been transforming into electrified transportation sector, hence, electric vehicles (EVs) are becoming ubiquitous. It has been predicted that Switzerland will have 15% EV penetration level by 2020 [19]. According to [20], the EVs penetration level will reach 62% in US by 2050. Till 2014, the US was leading the international market of EVs and plug-in hybrid electric vehicles (PHEVs) while China and Japan had second and third largest electric mobility markets respectively [21]. The leading position of US was mainly due to the incredible triumph of Tesla Model S launched in

2012. Tesla has recently revealed the quickest car of the world which would definitely obtain remarkable success in the future. Moreover, the prototype of Tesla Semi has also been revealed which is an all-electric Class 8 semi-trailer truck and it would form the basis of paradigm transition of heavy conventional trucks to electric trucks. The number of EVs has also been growing tremendously in other countries such as Korea, Norway, France, Netherlands, Sweden etc. and many efforts have been made to transform the existing transportation sector to electrified transportation sector.

Despite having many positive aspects of EVs such as fossil fuels independence, zero tailpipe emissions, higher efficiency, lower noise, increased passenger comfort, and higher safety level, there are many downsides that are inherent to EVs uncontrolled charging. Since the EVs utilize battery energy storage system to drive the electric motors for traction application, an electrical energy is required to charge battery storage systems that put an ample burden on the electric grid [22] which is already being noticed by system operators [23]. The simultaneous large-scale integration of EVs in the existing distribution power system remarkably increases the charging load which may lead to under voltages, higher losses, phase unbalance, load peaking, line and transformer overloads.

These days the widespread integration of EVs, especially in distribution system, has been an arisen topic to study since it produces considerable challenges due to their behavioral and locational uncertainties as mentioned above. However, these issues can significantly be mitigated by incorporating EV charging control strategies. In literature, several methods have been proposed to control the charging rates of EVs for secure and reliable operation of an electric grid. These methods can be classified into three control strategies i.e., centralized, decentralized, and autonomous charging control strategies which are described below.

2.1 Centralized Charging Control

In centralized charging control strategy, the EV owners submit charging requests to the EV aggregator that, utilizing central control unit, determines the optimal charging schedules by coordinating the charging patterns of the customers. The centralized charging architecture is shown in Figure 2.1.

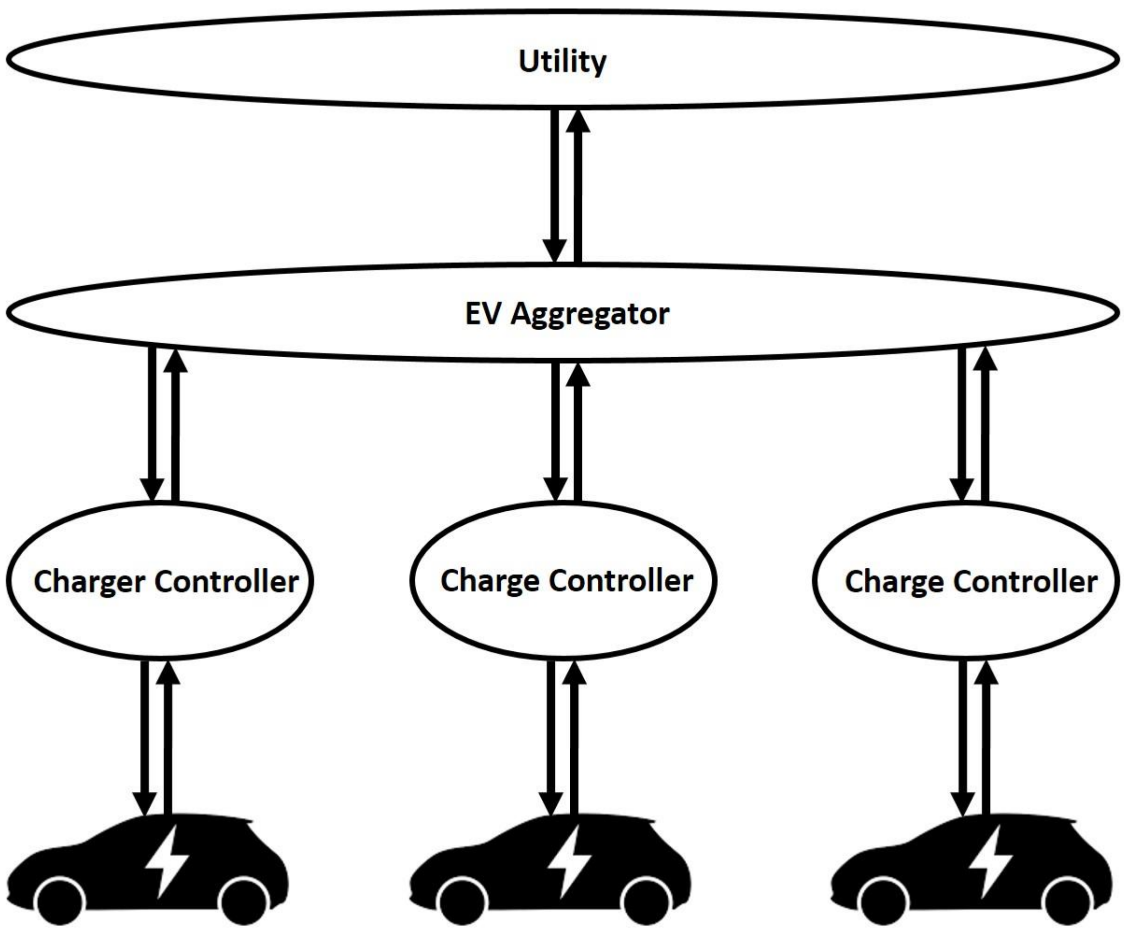

Figure 2-1 Centralized Charging Architecture

When an EV owner puts a charging request, smart charging control unit provides the current state-of-charge (SOC), required SOC, battery type, total battery capacity, and preferred plug-off time to the EV aggregator. The aggregator determines the optimal charging schedules based on the customer preferences, meanwhile, considering system-level concerns such as transformer overloads, feeder congestion, and system losses [24]. Such charge control strategies utilize power flow studies to determine the optimal charging schedules of EVs.

Since, the system data is obtained and sent to central control unit, and pre-dispatch and real-time scheduling are used to control the charging rates of EVs, a well-developed communication infrastructure is required for sending and receiving the control signals.

Many methods have focused on centralized charging control technique [12],[25]-[42]. EVs are utilized by aggregators to provide frequency regulation services [25],[26]. The charging and discharging rate of fleet of EVs is controlled to provide efficient frequency support in smart grid environment. A colored petri net based controller is proposed to regulate the charging rates of EVs catering their energy demands to provide frequency regulation services through aggregator [25]. In [26], an aggregator based EV storage system is developed for Danish power system to regulate instantaneous frequency fluctuations. In [27], a double-layer smart charging management algorithm is presented for EVs to satisfy both driver and power grid requirements. In the first level of proposed algorithm, capacity and power demand of transformers are determined, and shortest and most suitable charging point is found whereas the second level of algorithm regulates the charging rate of an EV based on user and grid requirements. The impact of EVs on an open loop radial distribution system is studied in [28]. The proposed approach estimates the charging time and location based on the demographical data and travel history and surveys. In [29], battery swapping based EV charging strategy using population-based heuristic approach (i.e., particle swarm optimization and genetic algorithm) is proposed to minimize the total charging cost, reduce system losses, and voltage violations. The optimal charging point and optimal charging rates are determined based on spot price. An algorithm based on dynamic estimation interpolation is developed to determine the charging schedules of PHEVs by considering valley-filling effect [30]. The user's cost is minimized by developing a price discount scheme.

In [31], a control strategy is developed that manages the charging points of EVs utilizing limited information. The proposed approach disconnects and reconnects EVs corresponding to corrective and preventive approach to mitigate the technical issues caused by EVs integration. The disconnection and reconnection of EVs adequately keep balance between the users charging requirements and mitigation of possible technical issues. An optimal bidding of ancillary services (i.e., regulations and spinning reserves) using fuzzy optimization through vehicle-to-grid coordination is proposed in [32]. In [33], receding-horizon optimization is proposed to formulate the EV charging problem considering current and foresee distribution network constraints over a particular charging horizon. The EVs charging is coordinated with the participation of fleet operator and distribution system operator to prevent distribution system congestion considering EV owner's driving requirements, charging price, and thermal limits of transformers and feeders [34]. In [12,35,36], distribution feeder losses are minimized. It has been observed that the feeder's load profile can be made smoother and voltage violations can be minimized [12],[36]. Moreover, the life of transformer can be prolonged [35],[37].

The algorithm for aggregators to schedule and dispatch EV fleets in the current wholesale energy market framework is proposed to maximize the energy trading profits [38]. In [39], a constrained mixed-integer linear programming is used to formulate the charging strategy for a smart charging station considering electricity pricing strategy which helps EVs to meet their charging requirements economically within the given deadline. A quasi-real-time management system is developed for EVs charging scheduling [40]. The EV aggregator minimizes the difference between the energy consumed by EVs and energy bought in the market while distribution system operator manages the grid constraints. In [41], a model predictive control is used to regulate the charging operations of EVs to minimize the charging cost as well as to meet grid requirements. In [42], a fuzzy optimization technique is proposed to maximize the profit of parking lot operators by coordinating the charging schedules of EVs considering the uncertainties related to market price and EV mobility. EV charging schedules are bid in a day-ahead market by parking lot operator and any deviations are minimized in a real-time market.

2.2 Decentralized Charging Control

In decentralized charging control strategy, EVs are equipped with smart charge controllers which calculate their optimal charging schedules. Figure 2.2 depicts a typical decentralized charging architecture.

When an EV gets connected in decentralized control framework, the smart controller obtains the current SOC of an EV battery. Concurrently, an EV owner needs to set the required SOC, expected plug-off time, and preferred charging rates. The utility or system operator sends the price signal to the smart charge control unit which performs the local optimization and optimal charge schedule is determined for an EV to minimize the overall charging cost. Decentralized control strategy requires reduced communication setup and low computational resources as compared to centralized control strategy.

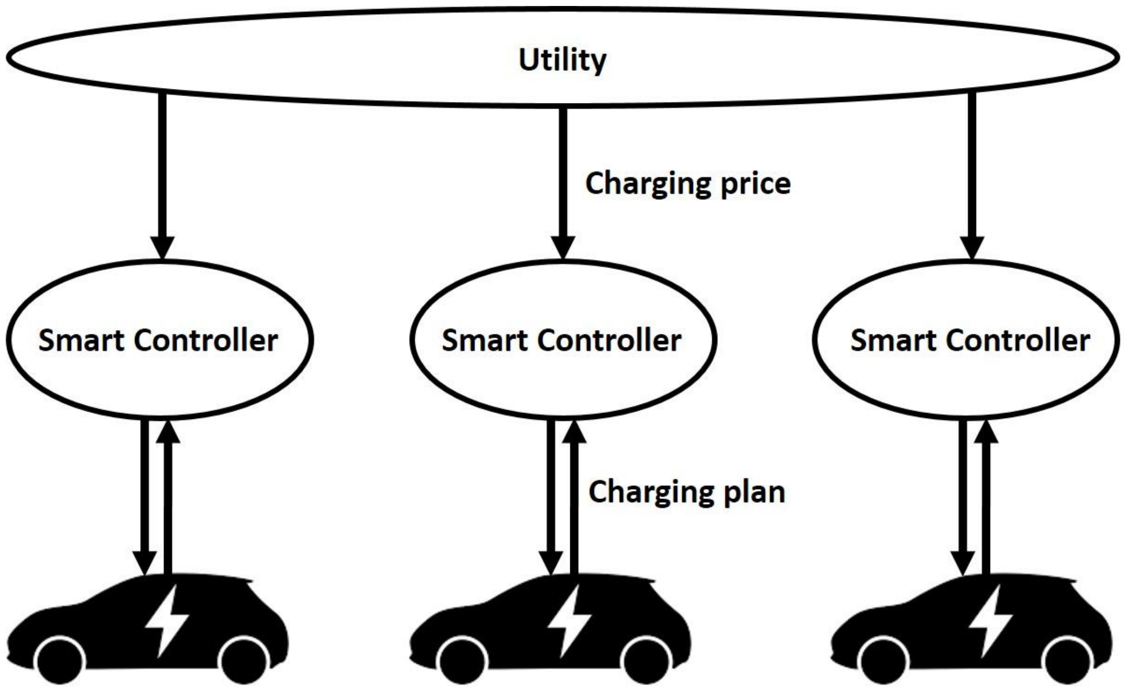

Figure 2-2 Decentralized Charging Architecture

Several works have considered decentralized charging strategies to schedule the charging periods of EVs [9],[43]-[55]. In [43], different charging strategies and power ratings have been investigated and compared based on their impact on electric grid, electric driving range, and the usage of local available generation. An apartment building, equipped with photovoltaic (PV) system, is considered to have multiple EVs which are coordinated without the need of optimization using limited prior knowledge. A concept of smart charging along with a vehicle-to-grid (V2G) strategy is employed to maximize the economic benefits [44]. V2G approach sells the energy to electricity market whereas smart charging strategy optimizes the charging time to maximize the overall profit while meeting the driving pattern feasibility. In [45], the charging schedules of a large number of PEVs, available at municipal parking station, are optimally managed using computational intelligence-based algorithms while taking real-world energy constraints into account.

A concept of non-cooperative games is used to formulate the strategy for PEVs charging coordination [46]. The proposed model assumes that PEVs are minimizing the charging cost and weakly linked with common market price. The charging rate of each PEV is optimally managed, at Nash equilibrium, with respect to an average charging pattern of all PEV strategies. In [47], the EV charging schedules are specified to ensure the valley-filing behavior using nested optimization. The framework of optimal power flow is built to include power system network constraints emerged due to the distributed EV charging points. The joint optimization of optimal power flow and EV charging requirements are decomposed and solved in a nested fashion. The decentralized algorithm is proposed to observe the valley-filling profile. In [48], the utility of charging service provider is maximized by coordinating the charging of EVs centrally using mixed-integer programming approach while satisfying the EV owners' charging requirements as well as transformer loading constraints. The proposed model is then decomposed for different parking decks by incorporating the Lagrangian relaxation approach, and some heuristic method is proposed for efficient implementation of proposed methodology. The flexibility of EVs charging load control is exploited by utilizing valley-filling approach [49]. The EV charging control problem is formulated as optimization problem with an objective of filling the valleys in load profiles. In the proposed algorithm, each EV needs to solve its local problem which requires less computational resources.

In [50], a scalable real-time greedy algorithm is developed to schedule the EVs charging process based on the SOC requirements at the departure time. The charging period of EVs is also shifted to low tariff hours specially to fill the night valleys, and EVs are scheduled to charge at discrete charging rates considering the EV owners' charging requirements. The proposed algorithm requires reduced communication since the EVs are scheduled separately at a plug-in time only. An EV charging scheduling process is formulated as a physical fair-queueing system [9]. A multi-server queueing system is used to model distribution sub-system where different EVs can charge at the same time. The proposed methodology ensures the fairness among the EVs irrespective of their locations in the distribution power system as well as prevents the distribution transformers overloading. In [51], shrunkenprimal-dual subgradient algorithm is proposed to control the EV charging process in a decentralized scheme. The EVs charging load is shifted to flatten the load profile by valley-filling while meeting EV owners' charging requirements without violating the system network constraints. An EV charger is designed using fuzzy logic control for decentralized scheme to alleviate the impacts of EV charging load on electrical grid [52]. The designed controller obtains the power grid parameters and EV battery type to control the charging current in order to mitigate the charging impact.

In [53], a charging algorithm is proposed to control the charging process of EVs to avoid overloading of components in distribution system. The charging process is modelled as convex optimization problem subject to feeder overload constraints. In [54], a convex relaxation optimization approach is proposed to schedule the EV charging process. An aggregator collects power demand of each EV and sends few signals on the basis of which selection probability adjustment is calculated for each EV. A hybrid centralized-decentralized charging scheme is proposed to minimize the charging cost while satisfying charging requirements [55]. The concept of leader-follower noncooperative Stackelberg game is used for interaction between charge controller and EVs.

2.3 Autonomous Charging Control

In contrast to centralized and decentralized control strategies, an autonomous charging control strategy does not require any kind of communication infrastructure as well as low computational burden is required which makes it most persuasive control technique. In this approach, some local parameters at the point of charging (POC) are measured and fed to EV charge controller as inputs to control the charging rates of EVs.

A number of methods have been developed to autonomously control the charging rates of EVs [56]-[67]. A voltage droop based EV charge controller is presented in [56]-[58]. The load profile is flattened by controlling the charging rates of EVs and the impact of proposed approach is determined based on electrically driven distances and the charging time of EVs [56]. Local voltage and next departure time are used to determine the charging rates of EVs. Different EV load models are described in [57]. These load models are simulated on the residential grid in Belgium, and their performances are compared on the basis of minimum charging rate achieved, system losses, and system voltage level. In [58], reactive power support is used to improve the system voltages especially for weak distribution grids having radial feeders. Although these voltage droop based charging techniques do not require any communication infrastructure, the issue of fairness among EVs at upstream vs. downstream nodes is not addressed. In [59],[60], the system frequency and SOC requirements for a next trip are used to design bidirectional EV charge controller. An autonomous V2G proposed control scheme provides distributed spinning reserves to electrical power system while satisfying the users' requirements. All the buses in the power system always have same frequency, however, they can have different voltage profiles. So, the impact of EVs would be not be mitigated unless the frequency of the system goes below a certain range. In [61], a rule based charging algorithm for PHEVs is proposed. The proposed algorithm uses houses daily load profiles to determine the minimum charging rate while ensuring the complete charging of batteries before the next use without charging during peak hours. The controller is solely based on the load profile of house and does not consider the system conditions. Moreover, the daily load profiles of houses are required to be fed to the controller.

Voltage based EV charge controllers are presented in [62]-[67]. A fuzzy logic based autonomous EV charge controller is proposed in [62] to avoid voltage violations in the distribution power system. The SOC of EV is also incorporated to determine the charging rate. In [63], the local load charging method is proposed to optimize the performance of EV charge controller. In addition to the nodal voltage, a pre-defined voltage-to-load sensitivity at POC and the SOC of EV battery are used to determine the charging rate. Since the system is continuously subjected to different loading conditions and possible reconfigurations, the sensitivity does not remain the same over a given period of time, which may lead to unfair EV charging. A nodal voltage is compared with the pre-set reference voltage to determine the charging rates of EVs [64]-[67]. An autonomous voltage feedback EV controller is presented [64] which compares the voltage at POC with the common reference voltage. The charging rate of EV decreases as the nodal voltage approaches reference set point. The upstream nodes have unintended higher charging rates since they have good voltage profiles as compared to downstream nodes. In [65], an instantaneous voltage at POC and SOC of EV battery are used to control the charging rates. Different reference voltages have been specified for different system nodes which may lead to unfair charging among EVs present at different locations in the distribution system since the system may change its configuration. Furthermore, the variations in the system loading condition may affect the fairness property. A real time digital simulator is used to implement the proposed controller [66]. The proposed controller adjusts the charging rates to avoid voltage violations while ensuring fairness among EVs. However, most of the system nodes are modelled as balanced which does not hold true for secondary distribution system and proposed controller may lead to unacceptable results. An adaptive voltage-feedback charge controller for EVs is proposed [67]. The proposed controller compares the input voltage with the pre-set reference voltage to avoid voltage violations, and determines the charging rate while satisfying the end-of-charge time requirements set by EV owners. Although it considers the fairness issue among the EVs but there is still a room of further improving the charging rates without violating network constraints. For example, at light loading condition, the controller unjustifiably limits the charging rates.

2.4 Voltage Sensitivity Analysis

The nodal voltage and frequency are commonly used local parameters especially in the distribution system. However, a relatively new concept of voltage-to-load sensitivity (i.e., a local parameter) has been developed to manage the voltage control in the distribution system, particularly when distributed generators (DGs) and EVs are integrated into the system. Several works have considered the concept of voltage sensitivity [68]-[75]. The commonly used approaches to calculate the sensitivity are discussed below.

2.4.1 Jacobian Matrix-Based Sensitivity Approach

In a classical way, the voltage sensitivities can be obtained from the inverse Jacobian matrix obtained after running the load flow analysis [68],[69]. The change in voltage due to change in real and reactive powers at the bus of interest, at a given operating point, can be determined using the following equations.

$$\boldsymbol{J} = \begin{bmatrix} \frac{\partial \boldsymbol{p}}{\partial \boldsymbol{\theta}} & \frac{\partial \boldsymbol{p}}{\partial \boldsymbol{v}} \\ \frac{\partial \boldsymbol{q}}{\partial \boldsymbol{\theta}} & \frac{\partial \boldsymbol{q}}{\partial \boldsymbol{v}} \end{bmatrix} \tag{2.1}$$

$$\boldsymbol{J}^{-1} = \begin{bmatrix} \frac{\partial \boldsymbol{\theta}}{\partial \boldsymbol{p}} & \frac{\partial \boldsymbol{\theta}}{\partial \boldsymbol{q}} \\ \frac{\partial \boldsymbol{v}}{\partial \boldsymbol{p}} & \frac{\partial \boldsymbol{v}}{\partial \boldsymbol{q}} \end{bmatrix} \tag{2.2}$$

$$\Delta v = \frac{\partial v}{\partial p}.\Delta p + \frac{\partial v}{\partial q}.\Delta q \tag{2.3}$$

where θ and v are voltage angles and magnitude vectors, respectively. The voltage sensitivities of the buses need to be updated whenever the state of network changes. For instance, if the network loading condition and/or network topology change, the previously determined sensitivities are to be re-calculated which, in turn, requires new load flows. Therefore, to implement this approach, the system should be fully observable which requires remote monitoring, and currently no such infrastructure exists in most distribution systems.

2.4.2 Perturb-And-Observe Power Flow Based Sensitivity Approach

In this approach, a load flow is run for two different states of system and a sensitivity is measured at the bus of interest [70]. So, a power flow is run for the current state of system and voltages are found. The active power (or reactive power), at the point of interest, is changed by a certain amount and the power flow is re-run to find the new voltages. In [71],[72], the load is added incrementally and series of power flow analyses are performed to calculate the sensitivities of all the nodes. These sensitivities are required to be updated every time the state of network is changed. Like in the inverse Jacobian matrix approach, a full observation of network is needed in perturb-and-observe approach, which requires communication channels.

2.4.3 Fitting Function Based Sensitivity Approach

In previous approaches, a system network needs to be observed continuously to update the voltage sensitivities. In order to eliminate the need of communication infrastructure, several different demand/generation scenarios are generated based on the planning data and extensive simulations are performed to determine the non-linear relationship of sensitivities [73]. To do so, a network topology, conductor parameters, rated capacities of system components, types of loads and generations are required to be known in advance. Furthermore, hundreds and thousands of load/generation scenarios are needed to model the daily, weekly, monthly, annually, and seasonal load variations. Then the surface fitting function is used to determine the sensitivity relationships for all the system nodes. Although this approach does not require remote monitoring, large computational resources are required to calculate the voltage sensitivities functions. Moreover, the accuracy of these functions depends upon the number as well as type of load/generation scenarios considered. Similarly, these functions become inapplicable when the system configuration is changed.

2.4.4 Quasi-Offline Parameter Measurement Based Sensitivity Approach

In this approach, some sensitivity parameters are determined offline while the actual sensitivity is calculated in a real-time analysis [74],[75]. A constant conductance and susceptance of an equivalent path between the DG and the transformer are used to find the coefficients of reactive power voltage magnitude and angle sensitivity functions [74]. However, the addition of load point or/and inclusion of DG unit along that path would effectively alter the parameters of equivalent path. In [75], sensitivity coefficients are obtained offline from historical data assuming that smart meters are installed which measure voltage as well as active and reactive power demands at each customer point. Linear model is then used to evaluate the voltages at customer nodes. This approach, however, requires updating the sensitivity coefficients when the network topology changes or/and the large load variations occur.

In this thesis, an adaptive autonomous EV charge controller is designed to control the charging rate based on the locally available system parameters such as, nodal voltage and its sensitivity to change in load. The proposed controller ensures the fairness among all the EVs irrespective of their charging locations by incorporating the SOC of EV batteries, and continuously measuring and updating the voltage sensitivity in real-time. Moreover, it avoids voltage violations in the distribution system by throttling the charging rates of EVs which can also significantly reduce line losses and avoid transformer overloads. This charging control scheme is simple as it does not require any kind of communication infrastructure and can accommodate high penetration of EVs in the existing electric grid without any upgrades. Since sensitivities are updated in real-time, this method is adaptive to variations in system conditions, such as system reconfiguration and existence of voltage control elements and DGs.

CHAPTER 3

PROPOSED ELECTRIC VEHICLE CHARGE CONTROLLER DESIGN

The technological advancements in transportation sector, growing trend of renewable energy sources, and new environmental policies have been escalating the integration of electric vehicles (EVs) into the distribution system that has a significant impact on the existing electrical grid. These impacts include feeder losses, voltage dips, and transformer overloads, which can greatly be reduced by controlling the charging rates of EVs since they offer higher flexibility in charging process due to relatively low distances driven and long standstill time [76]. As mentioned in Chapter 2, there are three charging schemes to control the charging rates of EVs. Centralized and decentralized strategies require communication infrastructure which is currently not available in many distribution systems and needs huge investments to be established. In contrast to these control strategies, no communication infrastructure is required in an autonomous control approach. Also, different methods to calculate the voltage-to-load sensitivity are summarized in Chapter 2.

In this thesis, a novel idea of online measuring sensitivity of voltage to load changes is introduced to implement an autonomous communication-free EV charge controller. The exact location of the EV charge controller is shown in Figure 3.1. It can be seen that the EV charge control unit is installed near the main electricity meter, hence, it can measure the total power consumption of the house without the need of any communication infrastructure. The proposed charge controller requires locally available system parameters, i.e., nodal voltage and sensitivity to determine the charging rate of an EV. It effectively keeps the voltage within the allowable range as defined by ANSI C84.1-2006 standard [77]. Furthermore, it ensures fairness among the EVs irrespective of their point-of-charging (POC) in the distribution power system.

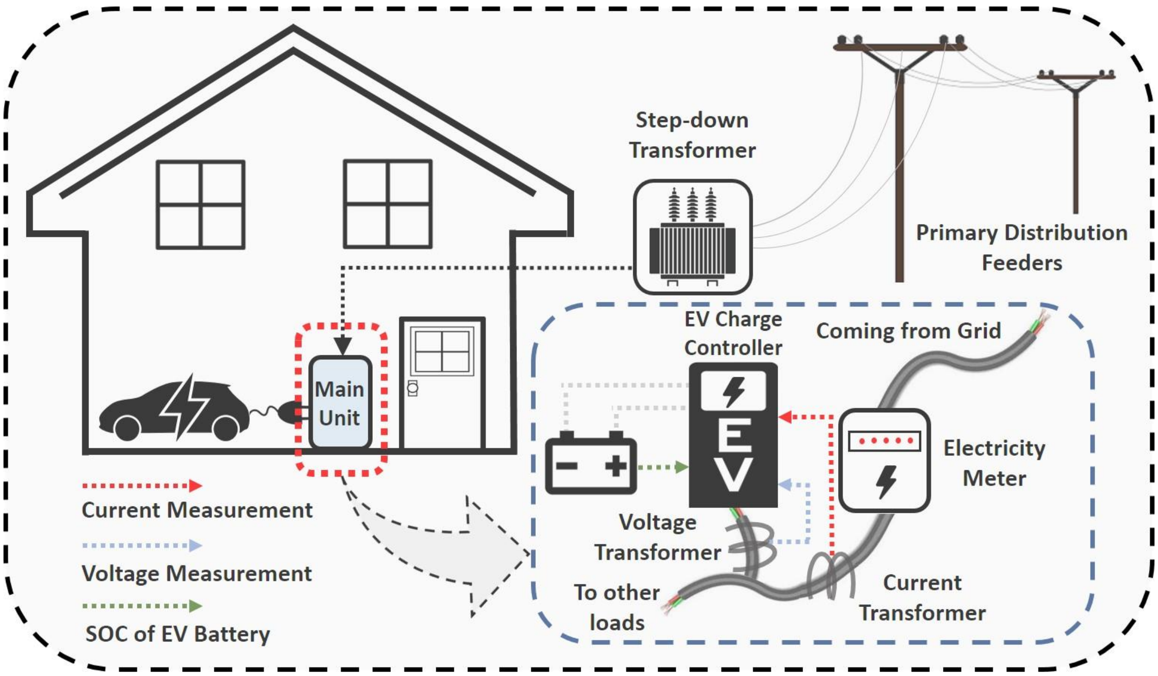

Figure 3-1 An EV Charge Control Unit.

3.1 Proposed Real-Time Online Measurement Based Sensitivity Approach

In this thesis, a novel method of online measuring voltage-to-load sensitivity is proposed that does not require the full observation of the network or any kind of remote monitoring. Furthermore, the sensitivity is updated automatically irrespective of the system topology or loading condition. In the proposed approach, the voltage and load (i.e., active or reactive or apparent power) at the bus of interest are measured and stored for the current state of the system. When the system load changes at the same bus, the new voltage and load are measured to calculate the sensitivity as follows.

$$\mu_i(t) = \frac{v_i(t)-v_i(t-\Delta t)}{p_i(t)-p_i(t-\Delta t)} \tag{3.1}$$

where v_i, p_i, and μ_i are the voltage, total load power, and sensitivity of i^{th} node respectively. A node here is defined as the house's point of connection to the distribution system. Note that the voltage and total load power are assumed to be measured in real-time, hence, the sensitivity is updated online. Four different scenarios can arise when measuring the sensitivity, as shown in Figure 3.2.

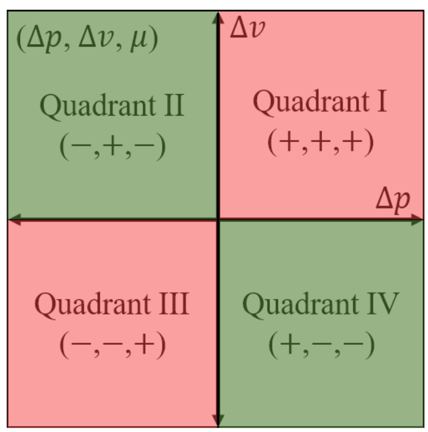

Figure 3-2 Different Scenarios for Sensitivity.

A) Negative Sensitivity Case *(i.e., Quadrants II and IV)*

The voltage at the bus of interest increases/decreases generally when the system load decreases/increases. In fact, the variations at the voltage of the bus is a very strong function of the variations in the load at that bus as compared to the variations at other buses [72]. Hence, the voltage sensitivities become negative. This case occurs most of the time since the sensitivity is updated only when there is a significant change in the load at a bus of interest (i.e., 10%) which results in negative sensitivity.

B) Positive Sensitivity Case *(i.e., Quadrants I and III)*

When the change in both voltage and load is positive or negative, the sensitivity becomes positive which means that the increase in load tends to increase the voltage or vice versa. In fact, the increase in load at the bus of interest tends to decrease the voltage at that bus. However, the significant decrease in loads at other buses of the system tends to increase the voltage at those buses as well as the bus of interest (i.e., bus where the load has been increased) which may result in overall increase in voltage at the bus of interest and, hence, the sensitivity becomes positive. However, it is very infrequent that such significant variations occur at different buses exactly at the same time when the time step is too small (say 10 seconds).

Moreover, it is worth noting that the voltage of bus of interest is far more sensitive to the change in load at that bus as compared to the variations in load at other buses [72]. So, in the proposed approach the sensitivity of the bus is calculated only when the change in load at that bus is greater than certain limit (i.e., 10%). So, it is very less likely that the increase/decrease in load results in increase/decrease in voltage. Even though it is very uncommon but still not impossible, so, such cases are considered outliers and previous sensitivities are retained which is completely reasonable. The question may arise that how much is that possible to have such big changes in the load to update the sensitivity over a specified time? Or are we going to lose some important variations in the system by not updating the sensitivity after every time step? These questions seem reasonable when the system under consideration is either a transmission system or primary distribution system where the variations in the load are quite small. However, in the secondary distribution system, at the level of houses, there are many such big changes mainly due to the cyclic nature of many loads such as air conditioning system, heating system, water heaters, refrigerators etc. and other turning on and off devices such as vacuum cleaners, hair dryers, dish washers, washing machines, clothes dryer, electric iron etc.

3.2 Electric Vehicle Charge Controller Design

In this research, an autonomous communication-free EV charge controller utilizing the novel idea of online measuring sensitivity of voltage to load changes is proposed. The purpose of the proposed charge controller is to throttle the charging rate of an EV based on the voltage at POC to prevent voltage violations in the system. This can also lead to reduced line losses and avoided overloads. In addition, fairness is a principal aspect of any EV charging strategy. In this context, fairness means that the limited system capacity is equally shared among all the EVs. In other words, EVs with the same state-of-charge (SOC) should be charged almost at the same rate irrespective of their locations in the system.

In the proposed charge control scheme, voltage sensitivity to changes in load power is factored in. The reason behind incorporating this sensitivity lies in the fact that nodes that have lower voltages are generally more sensitive to load power changes than those having higher voltages. Hence, EVs at downstream nodes will have lower voltage but higher sensitivity than those at upstream nodes. This will ensure fairness among the EVs at upstream, midstream, and downstream nodes. Moreover, EVs having lower SOC should be charged faster than EVs that have higher SOC. This feature has also been incorporated using an exponential function for SOC. Thus, the proposed EV charge controller receives the nodal voltage and voltage-to-load sensitivity as input signals and controls the charging rate of an EV. The charging rate of an EV can be determined as follows.

$$EP_j(t) = \begin{cases} \alpha_j + \{\beta_j . e^{-(\mu_i(t))(v_i(t)-v_r)}\} . e^{(1-\lambda_j)} & , v_i(t) \geq v_r \\ 0 & , \quad else \end{cases} \tag{3.2}$$

where EP_j is the expected charging rate of j^{th} EV, α_j is the minimum charging rate, v_r is the reference voltage (i.e., 0.955 p.u.), λ_j is the per unit SOC of an EV, and β_j is a controller parameter.

$$P_j(t) = \begin{cases} EP_j(t) & , \quad EP_j(t) < \overline{P_j} \\ \overline{P_j}(t) & , \quad EP_j(t) \geq \overline{P_j} \end{cases} \tag{3.3}$$

where P_j is the actual charging rate of an EV and $\overline{P_j}$ is the maximum charging rate of an EV. According to IEC 61851 standard, the minimum charging current limit is 6 A [78]. Therefore, a minimum charging rate is included in the charging equation. Also, it is worth noting that only one parameter is to be tuned which shows the simplicity of the proposed controller.

CHAPTER 4

SYSTEM INFORMATION AND DATA

4.1 Test Distribution System

To test the effectiveness of the proposed electric vehicle (EV) charge controller, a radial test distribution system shown in Figure 4.1 is used. This is an unbalanced three phase system with 17 primary nodes operating at nominal 12.47 kV line-to-line voltage. Each primary system node has a three-phase secondary distribution transformer that steps down the voltage from 12.47 kV to 0.22 kV. The secondary distribution transformer feeds 20 houses through different small feeders as shown in Figure 4.2. It can clearly be seen in the figure that the bus A is closer to the transformer as compared to bus E since it is fed by a feeder of length 100 ft. The parameters of primary and secondary distribution systems are given in Table 4.1.

4.2 Load Profiles

There are two types of loads in the system: 1) Non-controllable load and 2) Controllable load. The non-controllable load consists of the load of houses whereas controllable load includes EV load. Real data of several residential loads in the US with a ten-second resolution are used. The efficacy of proposed EV charge controller is assessed under different loading conditions such as light loading and heavy loading conditions. The purpose of these loading states is to take daily, monthly, and seasonal load variations into account.

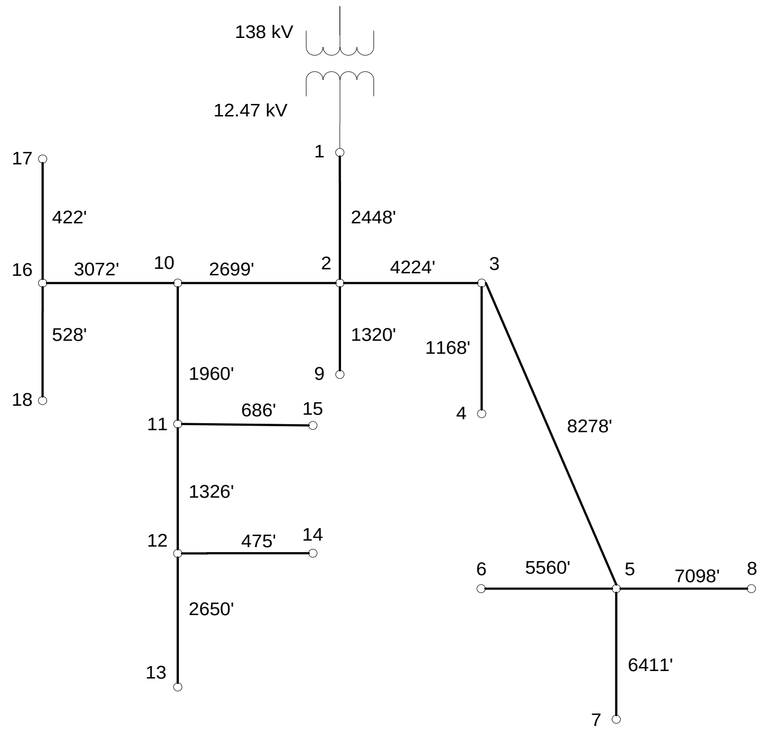

Figure 4-1 Primary Distribution Test System

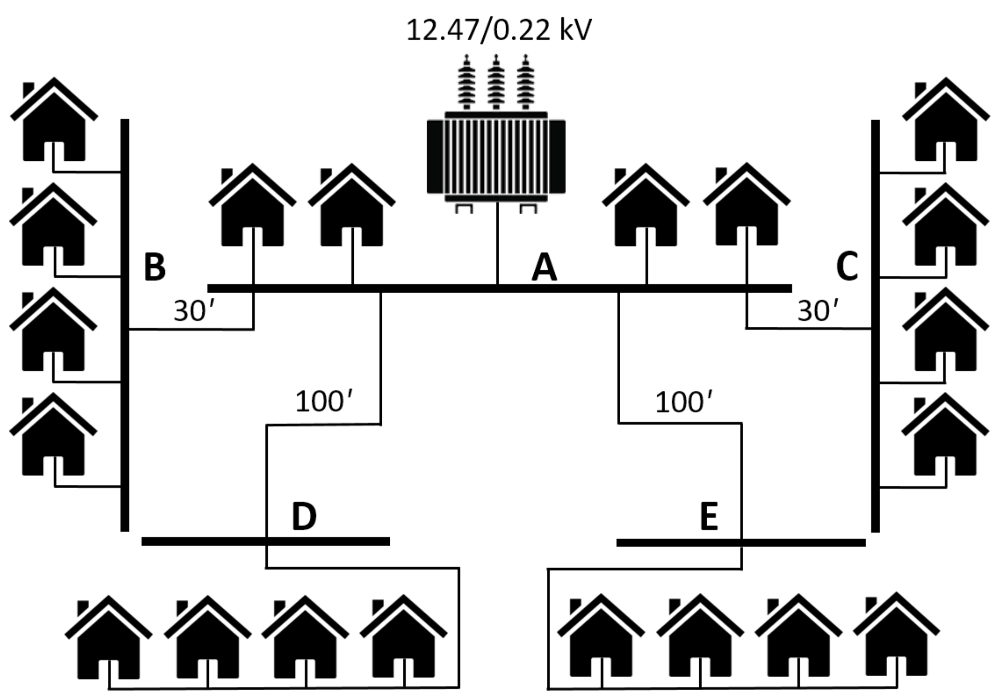

Figure 4-2 Secondary Distribution Network Topology

Table 4.1 Primary and Secondary Distribution System Parameters

Parameter	Value
Distribution phase conductor	ACSR 2
Distribution neutral conductor	ACSR 4
Max. current for primary conductors	180 amperes
Distribution service transformer	150 kVA
Secondary distribution conductor	350 Al, 4/0
System frequency	50 Hz
EV penetration	50%
No. of customers at secondary node	4

4.3 Electric Vehicles

In this thesis, two types of EVs, i.e., Nissan Leaf and Tesla S 70 are considered, and their charging loads (i.e., charging rates) are controlled using proposed EV charge controller. Generally, a load of single EV could be as large as, or even larger than, the load of a typical house. It is assumed that two houses will have one EV, i.e., 50% EV penetration level. The specifications of Nissan Leaf Model SV and Tesla Model S are provided in Table 4.2 and Table 4.3 respectively [79],[80]. The minimum charging rate (α) and controller parameter (β) for these EVs are provided in Table 4.4. The reason behind selecting these values of α is based on the assumption that the EVs must charge at least 20% to 25% of their maximum charging rates. Since β is the controller parameter, it needs to be tuned so that the EV charge controller ensures fairness among the EVs available at different nodes as well as their charging times are reasonable.

Table 4.2 Specifications of Nissan Leaf Model SV

Parameter	Value
Battery capacity	30 kWh
Maximum charging rate	6.6 kW
Initial battery SOC	40 %
Maximum mileage	107 mi

Table 4.3 Specifications of Tesla Model S

Parameter	Value
Battery capacity	70 kWh
Maximum charging rate	11.5 kW
Initial battery SOC	40 %
Maximum mileage	300 mi

Table 4.4 Controller Parameters for EVs

EV Type	α	β
Nissan Leaf Model SV	1.5	2.5
Tesla Model S	2.61	4.35

4.4 DIgSILENT PowerFactory

Since it is a three-phase unbalanced system, so an unbalanced power flow simulation must be run to find the nodal voltages and power flows. Therefore, a power system analysis tool is required to perform the load flow analysis. In this research, DIgSILENT PowerFactory [81] environment is used to implement and validate the efficacy of the proposed EV charge control scheme.

PowerFactory software is a powerful power system analysis tool that provides a framework to model the generation, transmission, distribution, and industrial grids. Moreover, renewables sources can easily be modelled and integrated into the power system. PowerFactory provides the state-of-the-art scripting feature, supported with a high-level programming language known as DIgSILENT programming language (DPL), which has been used to implement the proposed EV charge controller. The test distribution power system (only Node 02) created and simulated in DIgSILENT PowerFactory is shown in Figure 4.3. The secondary transformer is feeding five different loads, labelled as Load 02 A, Load 02 B etc. All the primary nodes have the same secondary system.

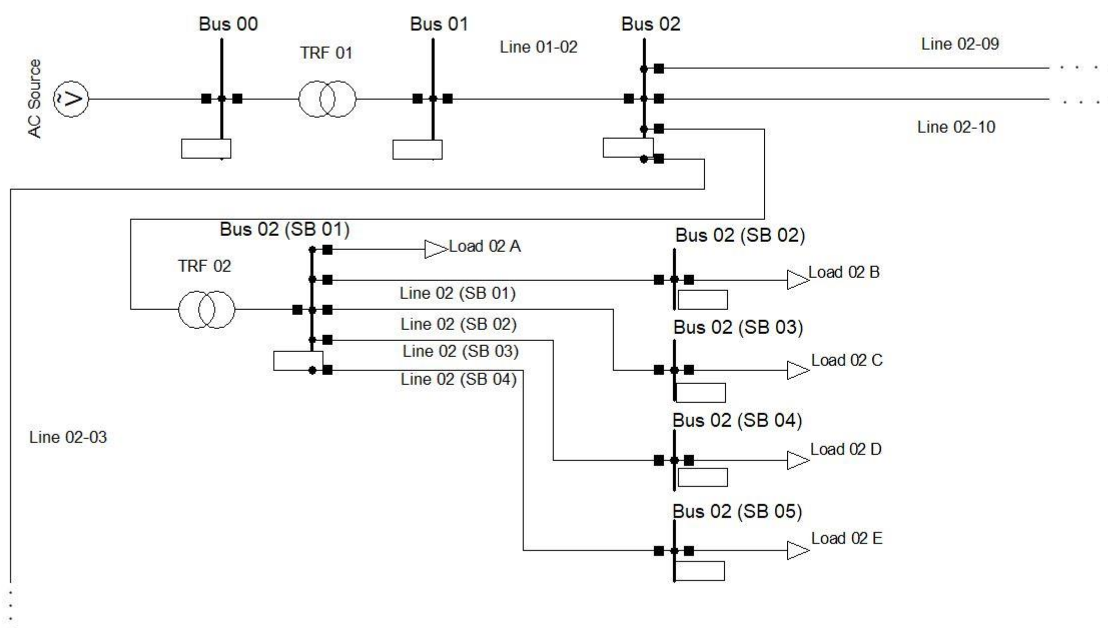

Figure 4-3 Test Distribution System in DIgSILENT PowerFactory

CHAPTER 5

RESULTS AND DISCUSSION

To validate the effectiveness of the proposed electric vehicle (EV) charge controller, an unbalanced three-phase test distribution system with eighty-five load buses is used. DIgSILENT PowerFactory software is used to employ the proposed controller in the test distribution system. It is assumed that two houses will have one EV, i.e., 50% EV penetration. It is further assumed that the test system follows a time-of-use (TOU) tariff structure having a lower tariff from 7 pm to 7 am. So, it is anticipated that EV owners will preferably charge their EVs during low tariff period. Certainly, EVs will not start charging exactly at the same time, and this fact is taken into account assuming that EV plug-in time follows Gaussian distribution with a mean and standard deviation of 8 pm and 1 hour respectively.

5.1 Base Case *(i.e., without EVs)*

To validate the performance of EV charge controller, different loading conditions, i.e., light and heavy loading conditions are considered. The main purpose of these loading conditions is to incorporate daily, monthly, and seasonal load variations. Since the system has many nodes, only few nodes have been selected which can provide enough details for the assessment of the proposed controller. Therefore, the results of upstream and downstream nodes have been described when needed. The nodes 2A and 6A are upstream while nodes 2E and 6E are downstream nodes. The load profiles of Node-6A and Node-6E are shown in Figures 5.1 and 5.2 for light and heavy loading conditions respectively. Similarly, the voltage profiles for the same nodes have been provided in the Figures 5.3 and 5.4. It can be clearly observed that the Node-6A always has higher voltage than that of Node-6E since these nodes are available on the same radial feeder (see Figures 4.1 and 4.2). Comparing voltage profiles during light and heavy loading conditions, the impact of loading on voltage drop is evident.

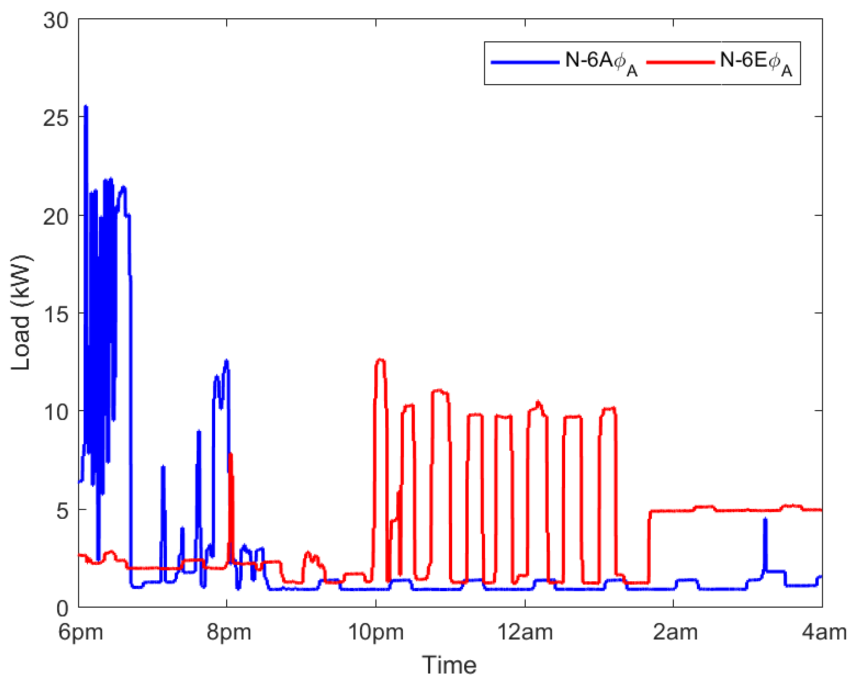

Figure 5-1 Load Profiles at Nodes 6A and 6E under Light Loading Condition without EVs

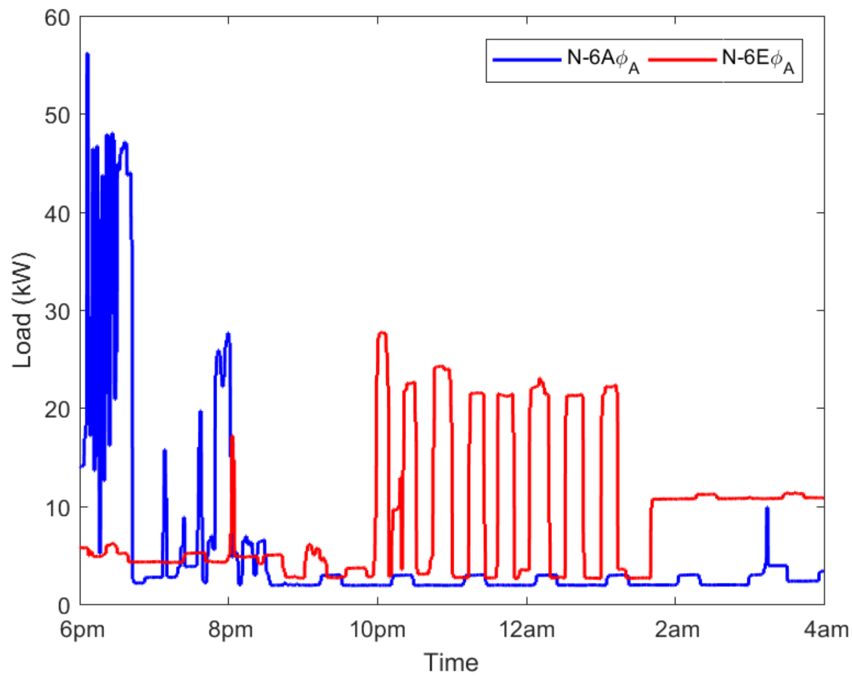

Figure 5-2 Load Profiles at Nodes 6A and 6E under Heavy Loading Condition without EVs

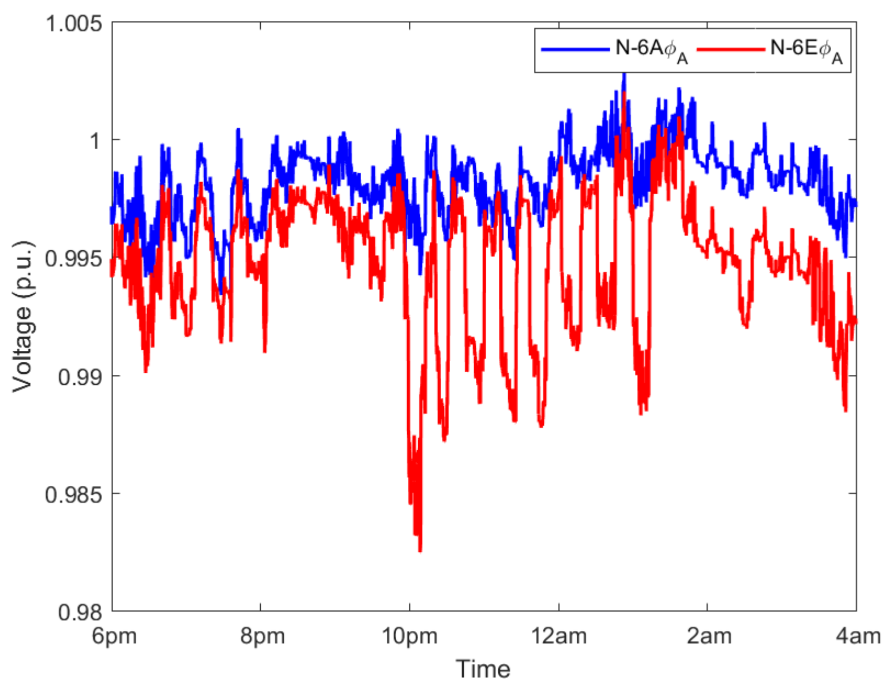

Figure 5-3 Voltage Profiles at Nodes 6A and 6E under Light Loading Condition without EVs

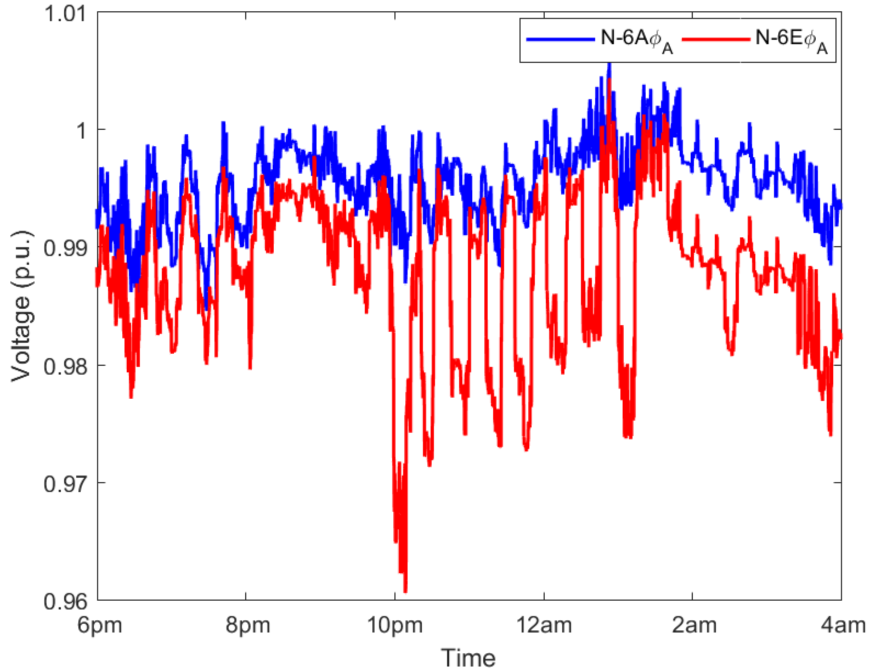

Figure 5-4 Voltage Profiles at Nodes 6A and 6E under Heavy Loading Condition without EVs

5.2 Opportunistic Charging

EVs start charging at their maximum charging rates in opportunistic charging scheme once they get connected into the system. This charging process is similar to a constant current charger case. This is considered as the benchmark case in terms of total charging time. The voltage profiles of some nodes, i.e., Node-4E (phase A), Node-16E (phase B), and Node-18D (phase C) are presented in Figures 5.5 and 5.6 for light and heavy loading conditions respectively. Under light loading condition no voltage violation occurs as shown in Figure 5.5. However, in heavy loading condition, the uncontrolled charging results in significant, unacceptable voltage drops. This dip in voltage occurs due to the addition of ample amount of EV charging load which persists for few hours as shown in Figure 5.6. After the EVs at these nodes are fully charged (at around 10 pm), the voltage profiles get slightly improved.

However, some EVs at other nodes are still charging, which impacts the voltages at these nodes. Hence, a charge controller is required.

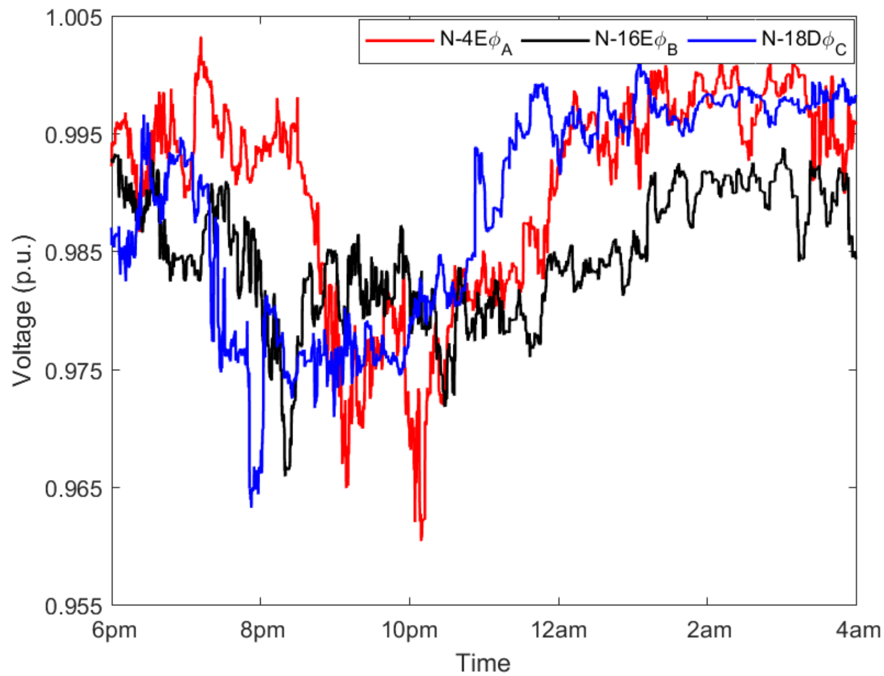

Figure 5-5 Voltage Profiles of Some Nodes with Opportunistic Charging under Light Loading Condition

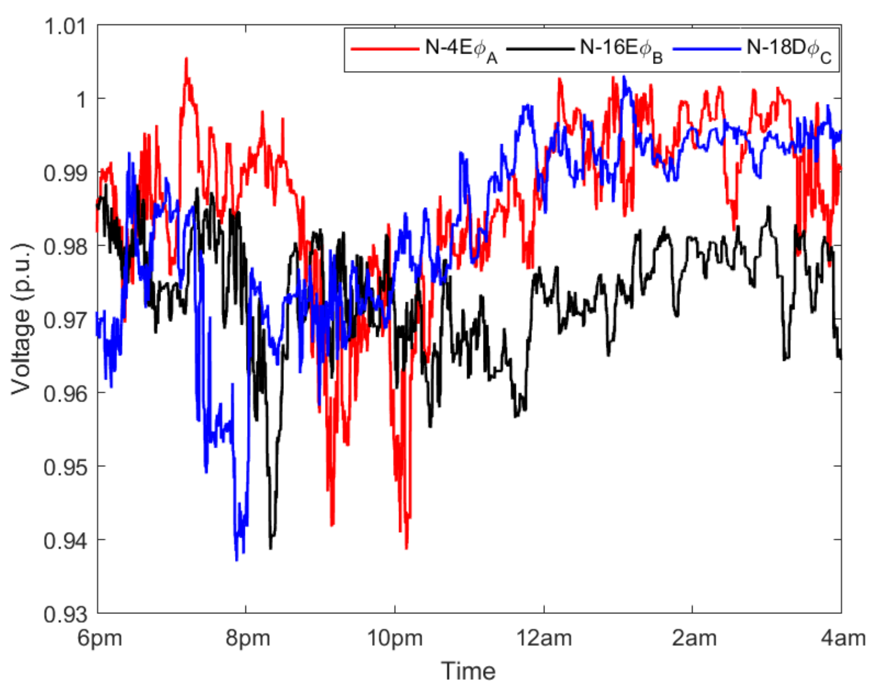

Figure 5-6 Voltage Profiles of Some Nodes with Opportunistic Charging under Heavy Loading Condition

5.3 Voltage Proportional Control Charging

In voltage proportional control strategy, a common pre-set reference voltage is set for all the nodes and the charging rate of an EV is controlled proportional to difference in nodal and reference voltages as shown in below.

$$EP_j(t) = \begin{cases} \gamma.(v_i(t) - v_r) & , \quad v_i(t) \geq v_r \\ 0 & , \quad else \end{cases} \tag{5.1}$$

where EP_j is the expected charging rate of j^{th} EV, γ is the proportional gain, and v_r is the reference voltage.

$$P_j(t) = \begin{cases} EP_j(t) & , \quad EP_j(t) < \overline{P_j} \\ \overline{P_j}(t) & , \quad EP_j(t) \geq \overline{P_j} \end{cases} \tag{5.2}$$

where P_j is the actual charging rate of an EV and $\overline{P_j}$ is the maximum charging rate of an EV. The reference voltage is set to 0.955 p.u. while constant proportional gain (γ) is selected to be 165. Using this charging technique voltage violations can be avoided as shown in Figure 5.7. However, it does not ensure fairness among EVs available at different locations in the system. As upstream nodes have higher voltage as compared to downstream nodes, hence, EVs at these nodes are unintentionally charged faster which is evident from Figures 5.8 and 5.9. The minimum charging time, maximum charging time, average charging time, and standard deviation of charging time are provided in Table 5.1. There are eighty-five secondary nodes, each phase having four houses. Since 50% EV penetration is assumed, there are 510 EVs in the system. The minimum charging time represents the charging time of the EV that is charged earliest while the maximum charging time represents the charging time of the EV that is charged latest. It can be seen from Table 5.1 that there is a difference of around two hours between the earliest and the latest EVs charged which means that the controller does not ensure fairness among the EVs available at different nodes. Four of the EVs available at downstream nodes do not charge completely since they have lower nodal voltages that lead to slow charging.

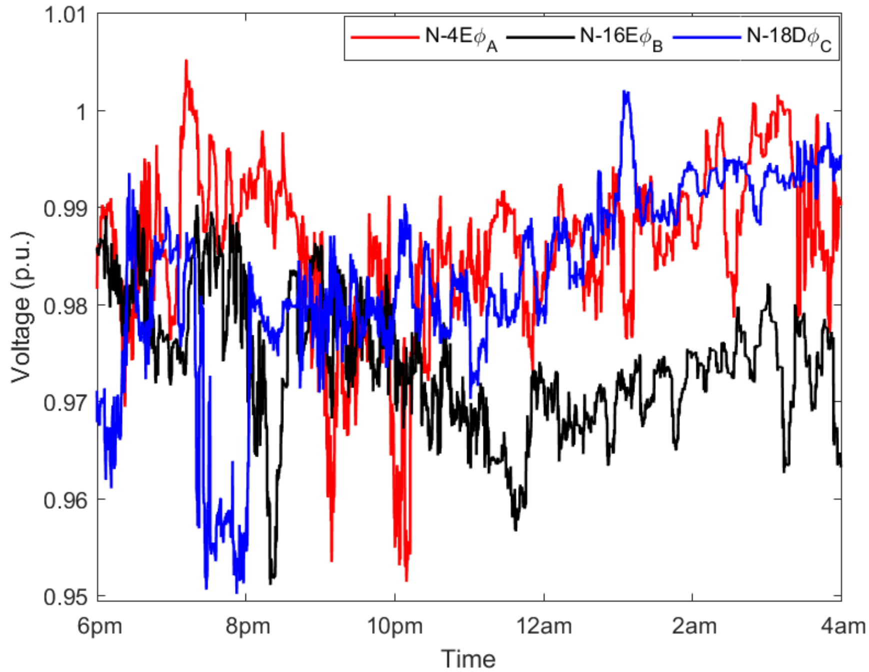

Figure 5-7 Voltage Profiles of Some Nodes with Proportional Charging under Heavy Loading Condition

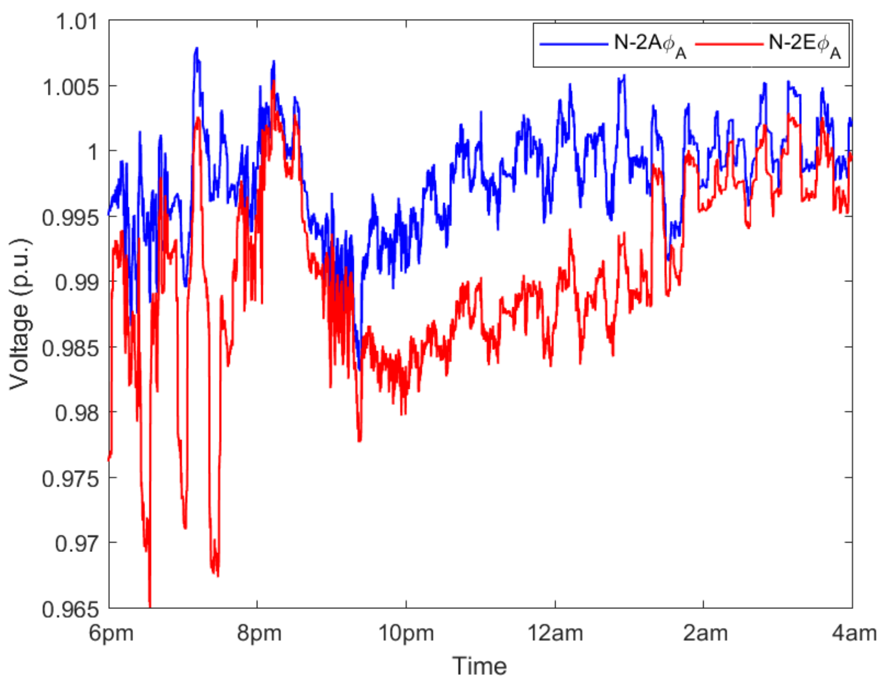

Figure 5-8 Voltage Profiles of Nodes 2A and 2E with Proportional Charging under Heavy Loading Condition

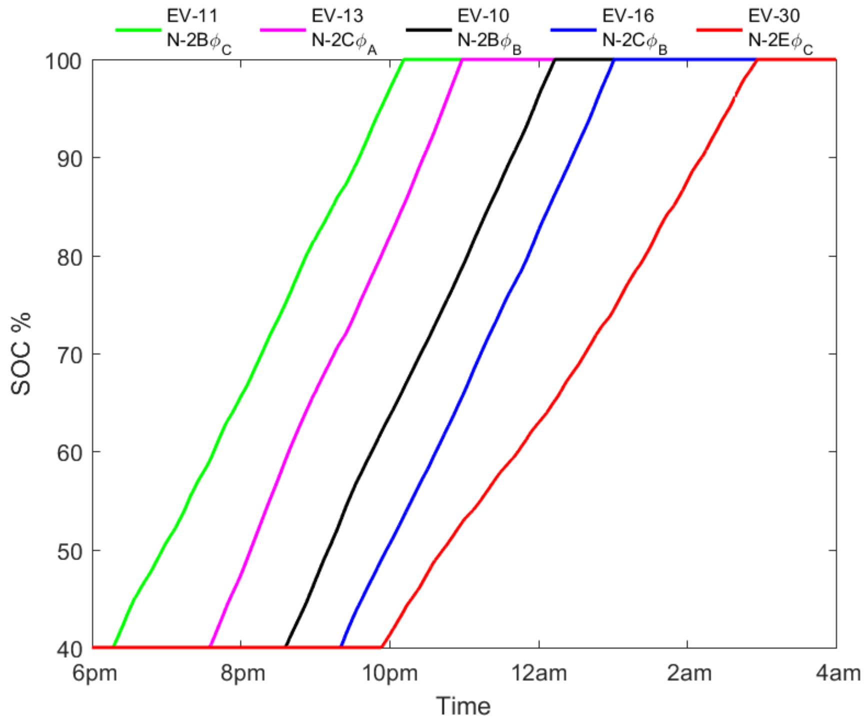

Figure 5-9 SOC of EVs at sub-nodes of Node 2 with Proportional Charging under Heavy Loading Condition

Table 5.1 Charging Time of EVs with Proportional Charging

Loading Condition	Min. Charging Time	Max. Charging Time	Average Charging Time	Std. of Charging Time
Light	2.753 hrs.	4.719 hrs.	3.457 hrs.	0.467 hrs.
Heavy	2.781 hrs.	-	-	-

5.4 Adaptive Voltage Feedback Charging

As mentioned earlier that voltage proportional control charging strategy charges the EVs available at upstream nodes faster as compared to EVs at downstream nodes. In [67], an adaptive voltage-feedback EV charge controller is presented to address the issue of fairness among EVs. Moreover, it avoids the voltage violations in the system due to EV charging load. This controller is considered as a benchmark in terms of fairness. The control structure is described below:

$$EP_j(t) = \begin{cases} \overline{P_j} - (\overline{P_j} - \alpha_j)(e^{-k(v_i(t)-v_r)}.\, e^{(1-\lambda_j)} & , v_i(t) \geq v_r \\ 0 & , \quad else \end{cases} \tag{5.3}$$

where EP_j is the expected charging rate of j^{th} EV, $\overline{P_j}$ and α_j are the maximum and minimum charging rates of adaptive voltage feedback controllers, and k is the controller parameter.

$$P_j(t) = \begin{cases} EP_j(t) & , \quad EP_j(t) < \overline{P_j} \\ \overline{P_j}(t) & , \quad EP_j(t) \geq \overline{P_j} \end{cases} \tag{5.4}$$

where P_j is the actual charging rate of an EV and $\overline{P_j}$ is the maximum charging rate of an EV. The voltage profile of some nodes, i.e., Node-2A, Node-2E, Node-6A, and Node-6E are shown in Figures 5.10-5.13. It can clearly be seen from these figures that this controller prevents voltage violations to happen. The SOC of EVs located at sub-nodes of Node-2 and Node-6 are shown in Figures 5.14-5.17. Some of the important charging parameters are tabulated in Table 5.2. Although the voltages at different nodes are quite different but the EVs are charging almost at the same time since the standard deviation is much lower as compared to the voltage proportional charge controller case which means that the adaptive voltage feedback controller ensures the fairness among the EVs available at different nodes of the system. However, the charging rates could be further improved since the voltages are still in a good range.

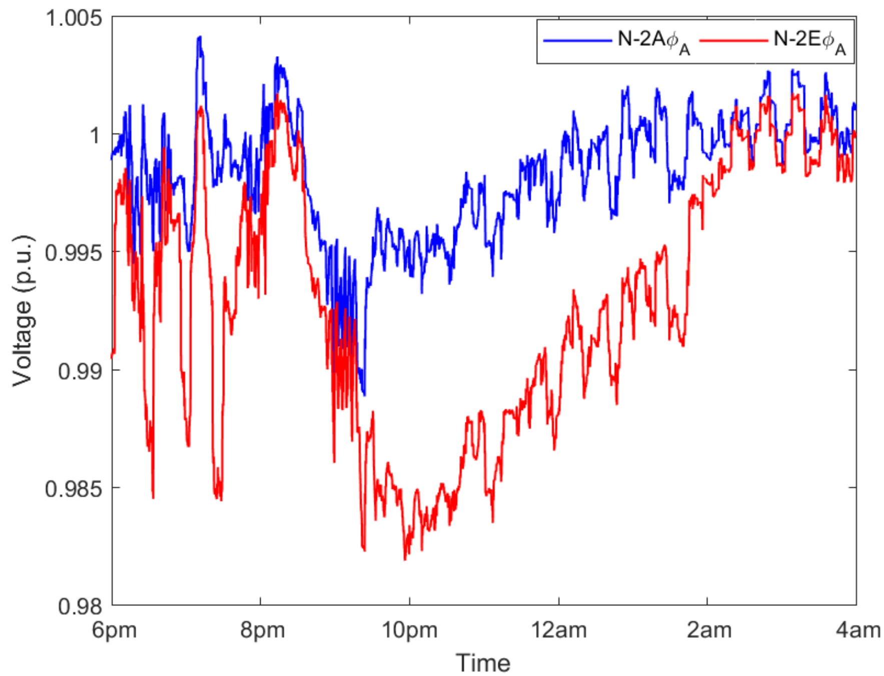

Figure 5-10 Voltage Profiles of Nodes 2A and 2E with Adaptive Voltage Feedback Charging under Light Loading Condition

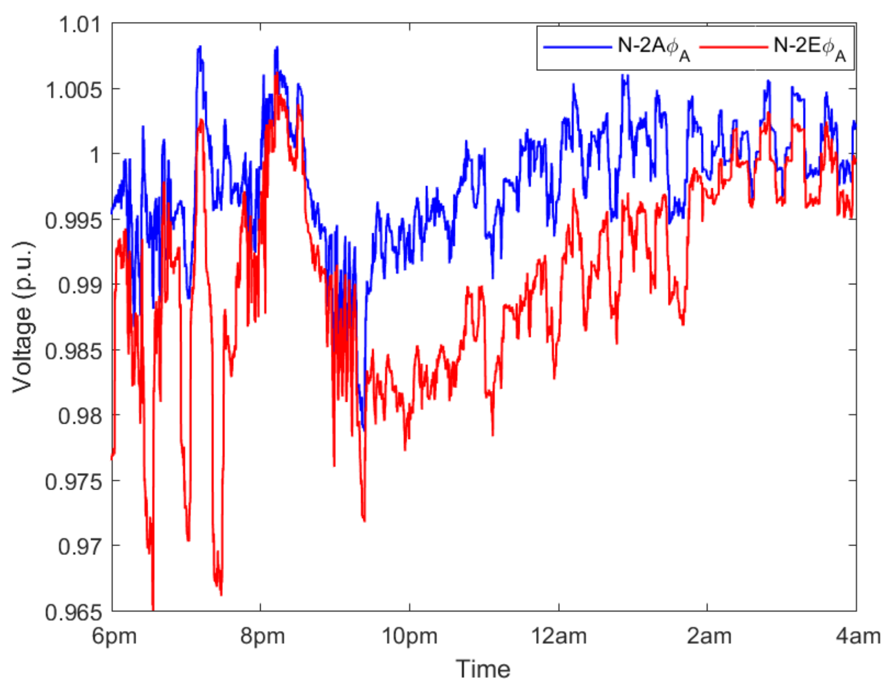

Figure 5-11 Voltage Profiles of Nodes 2A and 2E with Adaptive Voltage Feedback Charging under Heavy Loading Condition

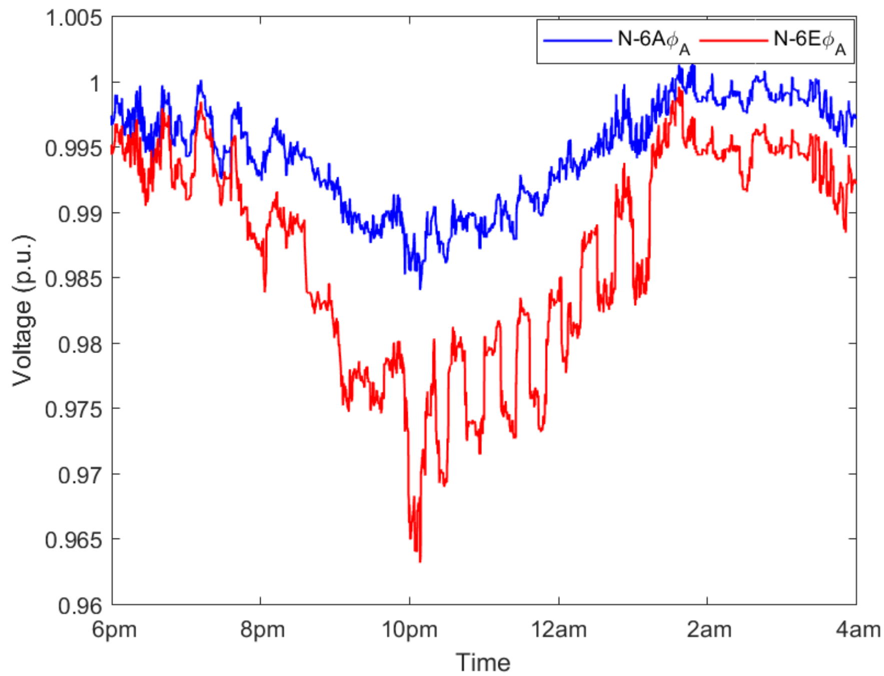

Figure 5-12 Voltage Profiles of Nodes 6A and 6E with Adaptive Voltage Feedback Charging under Light Loading Condition

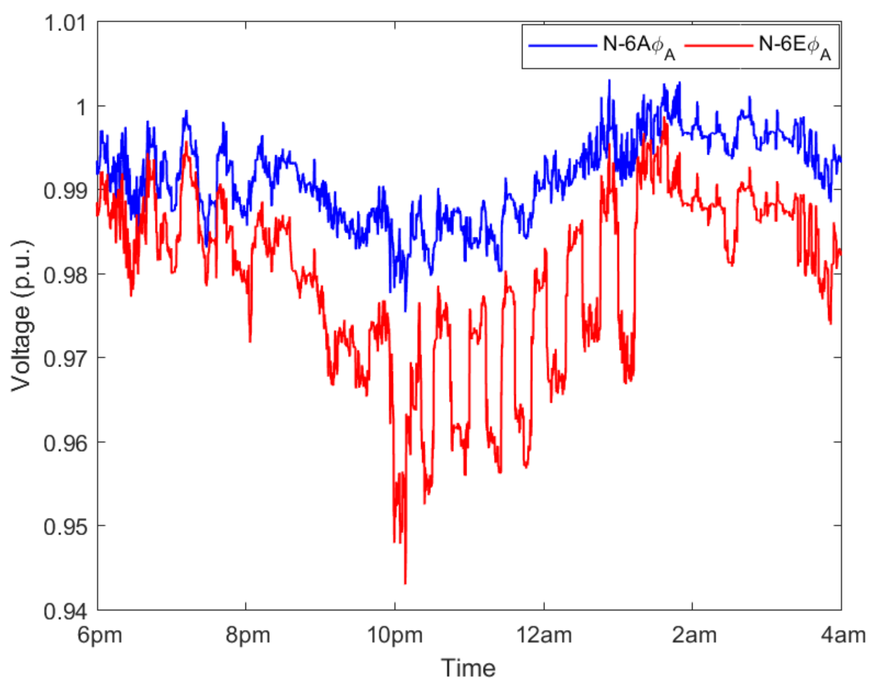

Figure 5-13 Voltage Profiles of Nodes 6A and 6E with Adaptive Voltage Feedback Charging under Heavy Loading Condition

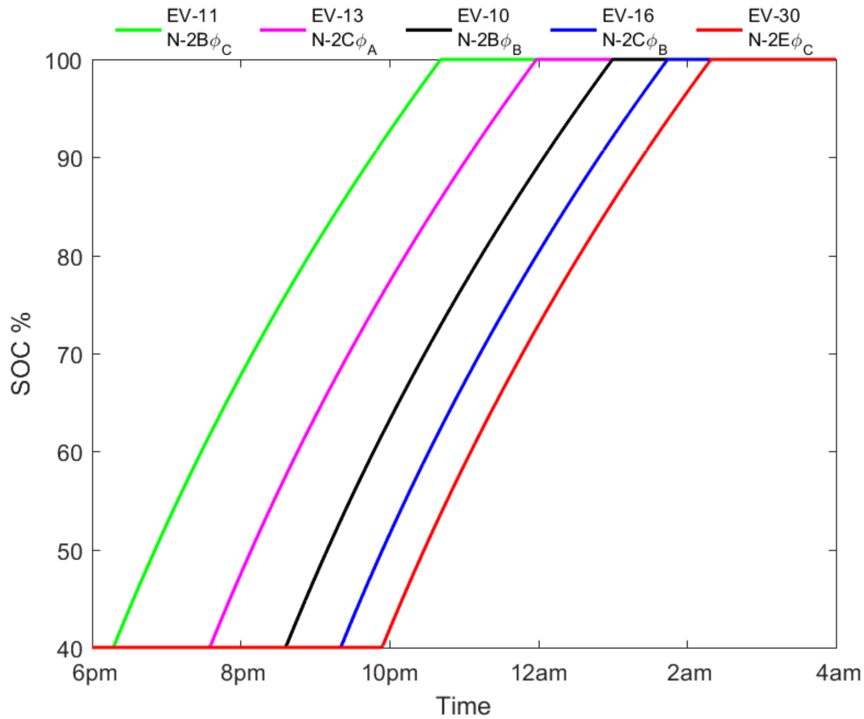

Figure 5-14 SOC of EVs at sub-nodes of Node 2 with Adaptive Voltage Feedback Charging under Light Loading Condition

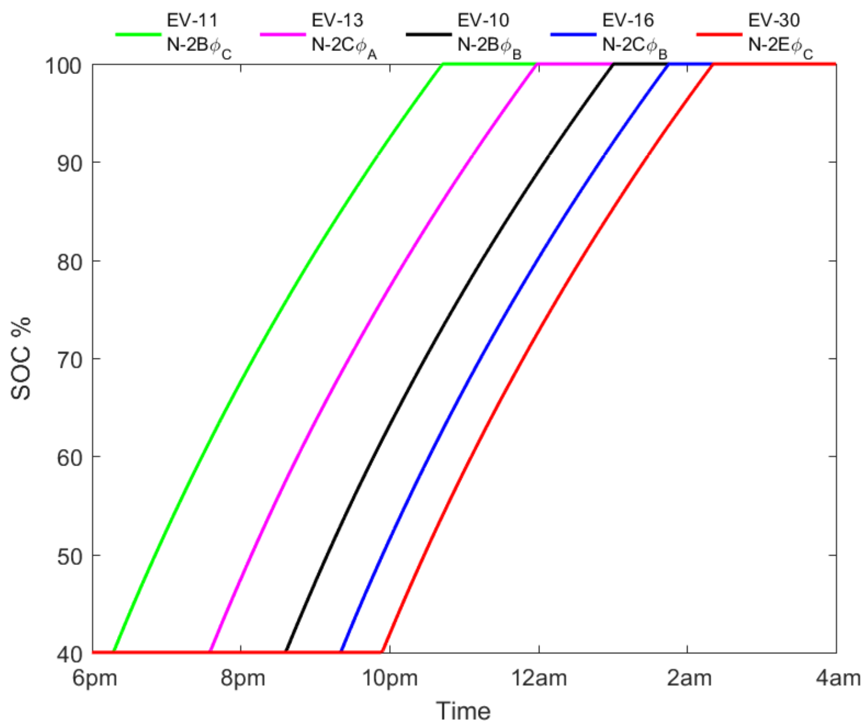

Figure 5-15 SOC of EVs at sub-nodes of Node 2 with Adaptive Voltage Feedback Charging under Heavy Loading Condition

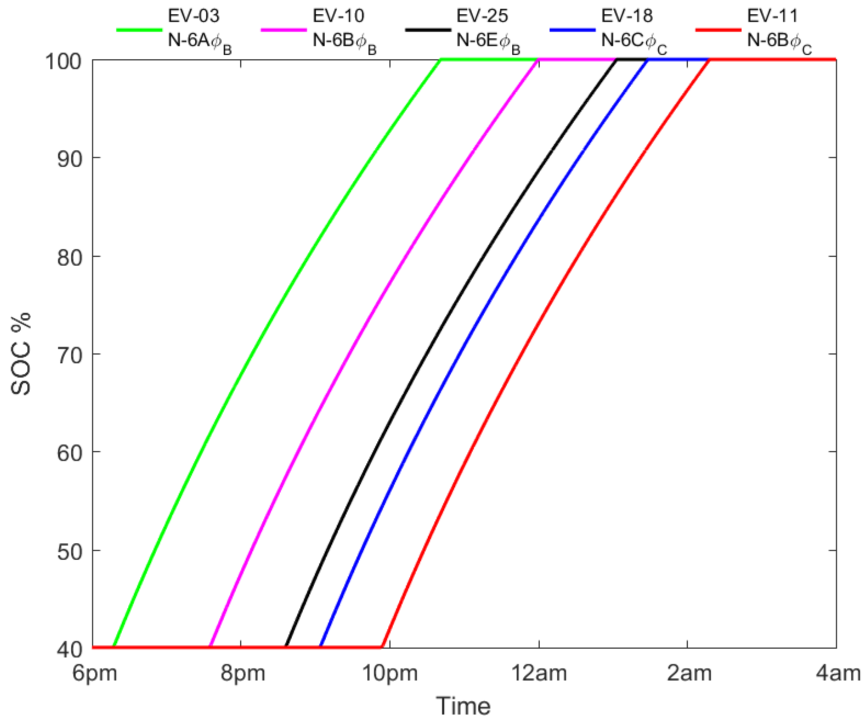

Figure 5-16 SOC of EVs at sub-nodes of Node 6 with Adaptive Voltage Feedback Charging under Light Loading Condition

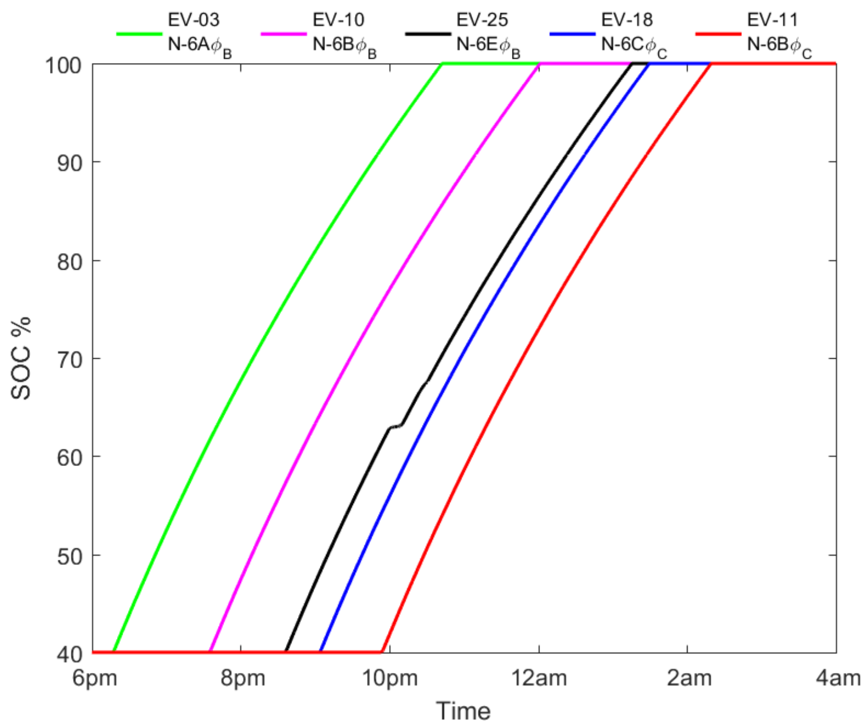

Figure 5-17 SOC of EVs at sub-nodes of Node 6 with Adaptive Voltage Feedback Charging under Heavy Loading Condition

Table 5.2 Charging Time of EVs with Adaptive Voltage Feedback Control Charging

Loading Condition	Min. Charging Time	Max. Charging Time	Average Charging Time	Std. of Charging Time
Light	3.944 hrs.	4.025 hrs.	3.983 hrs.	0.0174 hrs.
Heavy	3.944 hrs.	4.897 hrs.	4.031 hrs.	0.1112 hrs.

5.5 Proposed Voltage-and Sensitivity-Responsive Charging

In the proposed EV charge controller, a nodal voltage and voltage-to-load sensitivity are used to determine the charging rate of an EV, without the need of any kind of communication infrastructure since local parameters are being utilized. The concept of voltage and its sensitivity to change in power is used to ensure the fairness among the EVs available at upstream and downstream nodes. The node having good voltage is less sensitive to change in load than that having a low voltage which can be clearly observed in Figures 5.18 and 5.19. The voltage profiles of Node-2A, Node-2E, Node-6A, and Node-6E are shown in Figures 5.20-5.23 respectively. The proposed controller effectively controls the charging rate of EVs to avoid voltage violations due to EV charging load which can be observed in Figure 5.24. The SOCs of EVs available at Node-2 and Node-6 are given in Figures 5.25-5.28. The histogram of charging time difference between proposed and adaptive voltage feedback controller, provided in [67], is shown in Figure 5.29. The proposed controller charges the EVs faster as compared to adaptive voltage feedback controller in both light and heavy loading conditions which means that the proposed controller is squeezing the system to a higher degree. The minimum charging time difference is about 14 minutes and it could be as long as 28 minutes which proves the effectiveness of the proposed controller. Moreover, it ensures more fairness as compared to voltage feedback controller under heavy loading condition since it has lower standard deviation as given in Table 5.3. The minimum charging time for heavy loading condition is lesser when compared to light loading condition which seems anomalous. As mentioned earlier, the minimum charging time represents the charging time of the EV that is charged earliest, so the minimum charging time could be smaller in case of heavy loading condition as long as the difference is very small. However, the average charging time must be smaller in case of light loading condition to prove the effectiveness of the proposed controller.

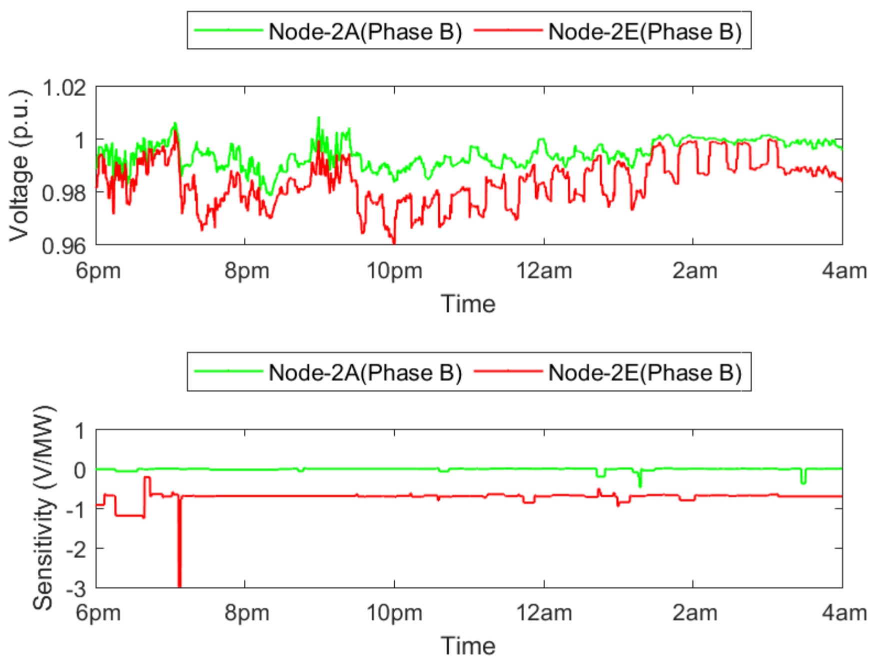

Figure 5-18 Voltage and Sensitivity of Node-2A and Node-2E under Heavy Loading Condition

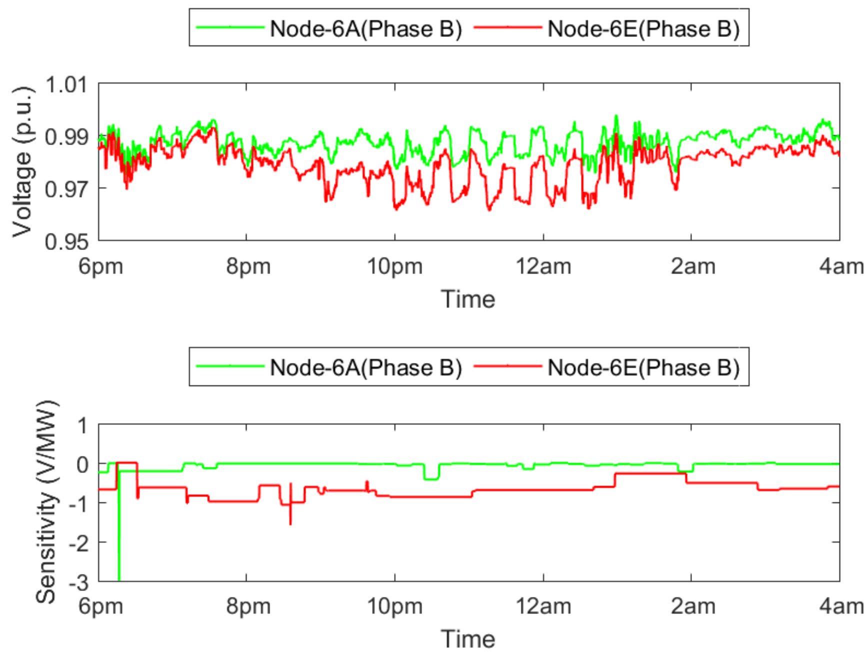

Figure 5-19 Voltage and Sensitivity of Node-6A and Node-6E under Heavy Loading Condition

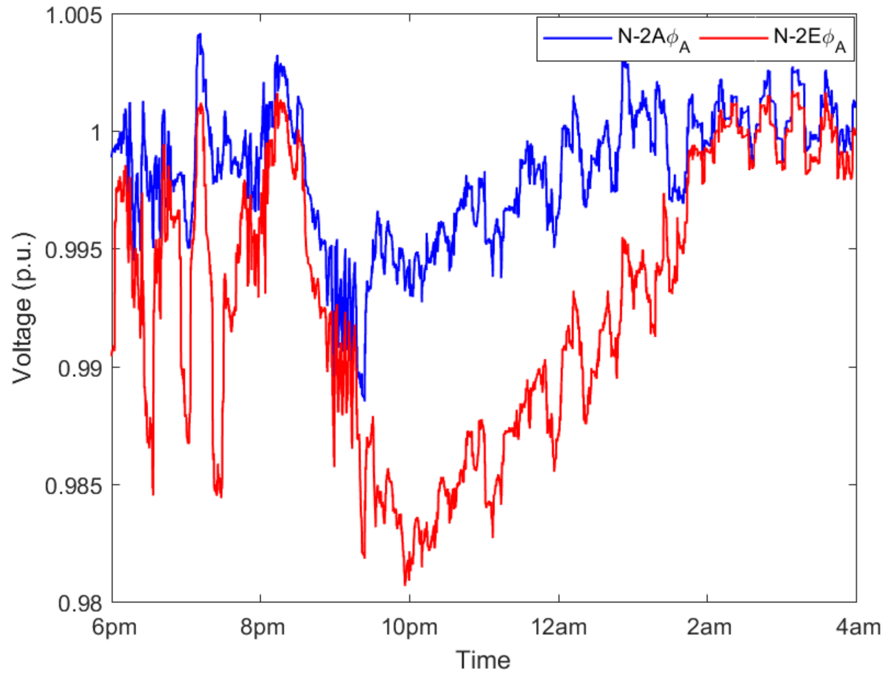

Figure 5-20 Voltage Profiles of Nodes 2A and 2E with Proposed Controller under Light Loading Condition

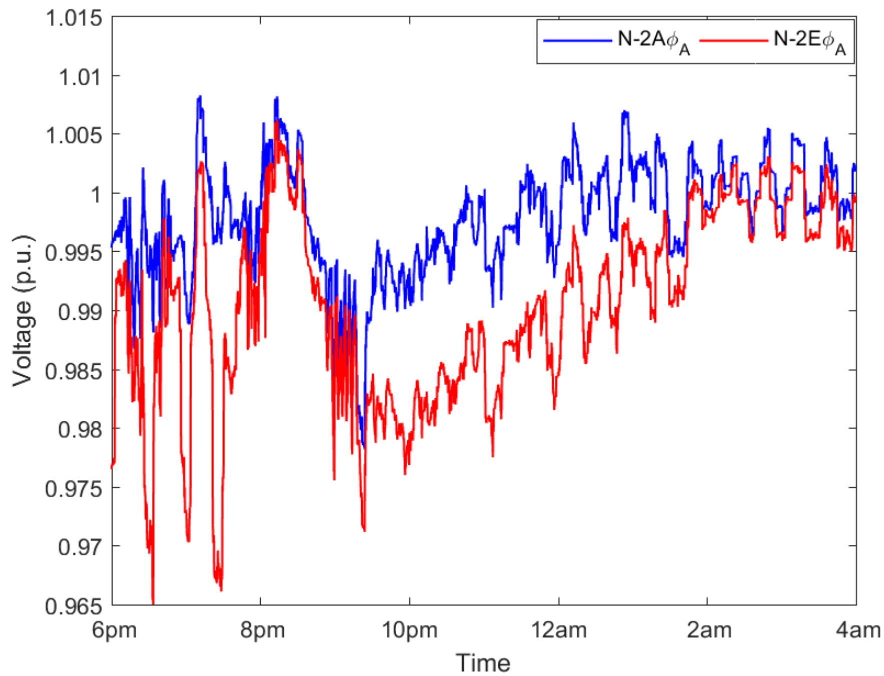

Figure 5-21 Voltage Profiles of Nodes 2A and 2E with Proposed Controller under Heavy Loading Condition

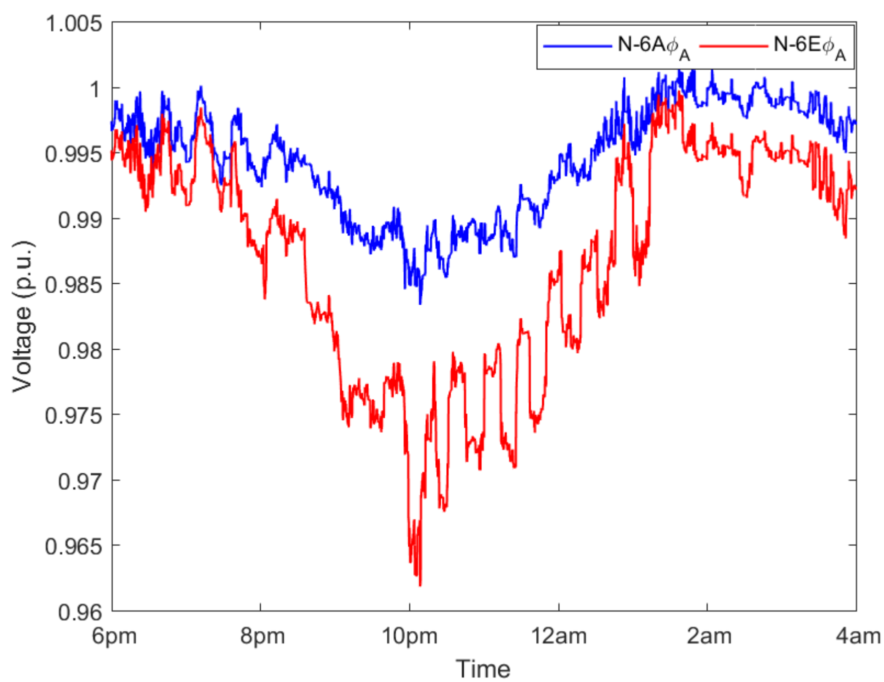

Figure 5-22 Voltage Profiles of Nodes 6A and 6E with Proposed Controller under Light Loading Condition

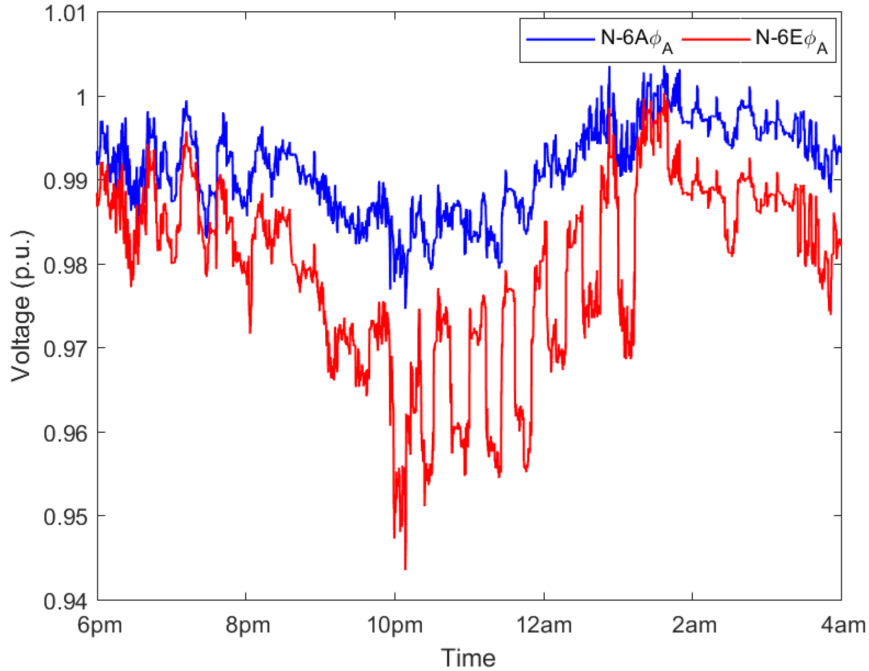

Figure 5-23 Voltage Profiles of Nodes 6A and 6E with Proposed Controller under Heavy Loading Condition

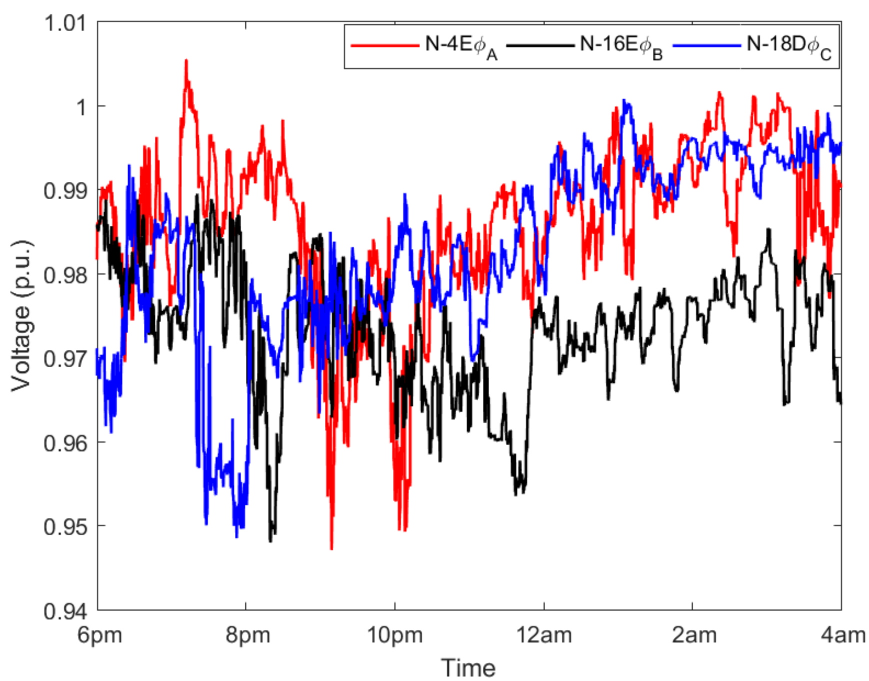

Figure 5-24 Voltage Profiles of Some Nodes with Proposed Controller under Heavy Loading Condition

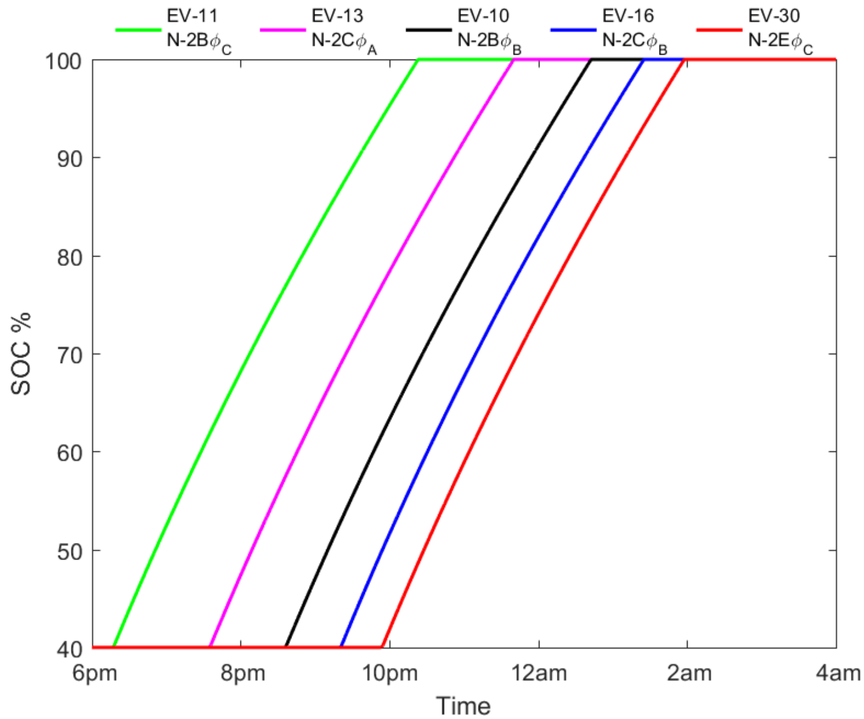

Figure 5-25 SOC of EVs at sub-nodes of Node 2 with Proposed Controller under Light Loading Condition

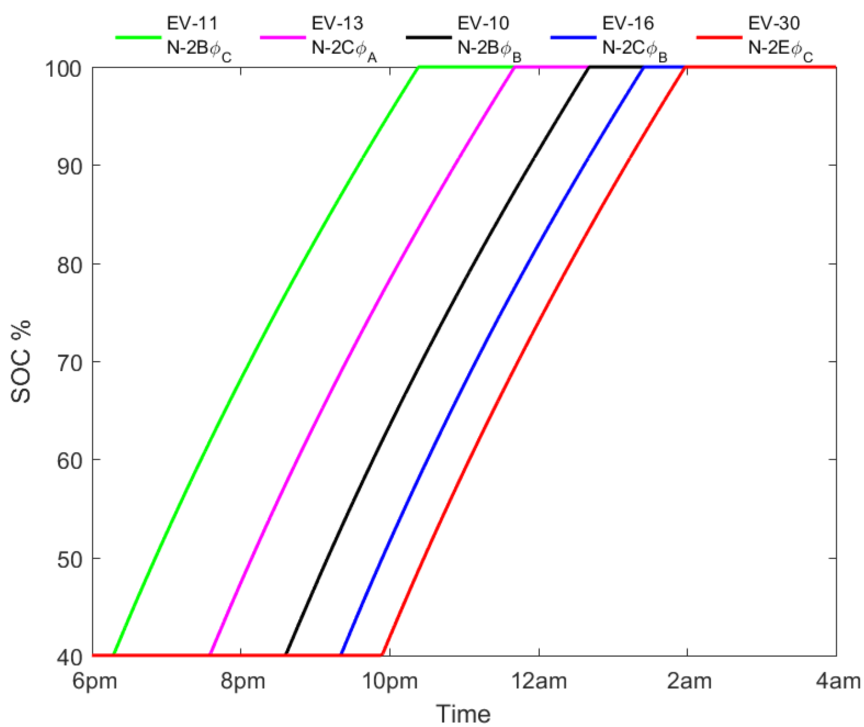

Figure 5-26 SOC of EVs at sub-nodes of Node 2 with Proposed Controller under Heavy Loading Condition

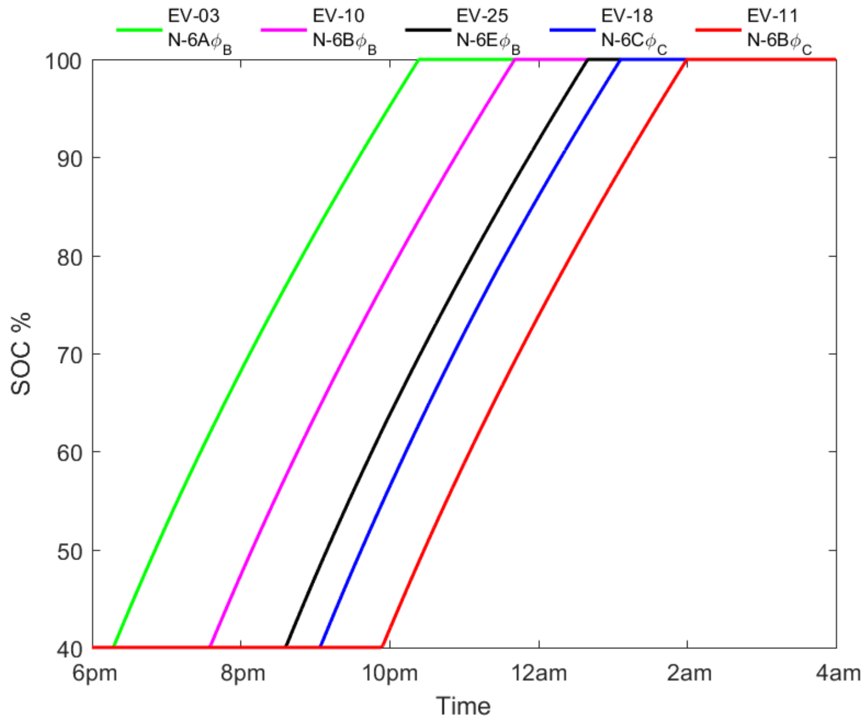

Figure 5-27 SOC of EVs at sub-nodes of Node 6 with Proposed Controller under Light Loading Condition

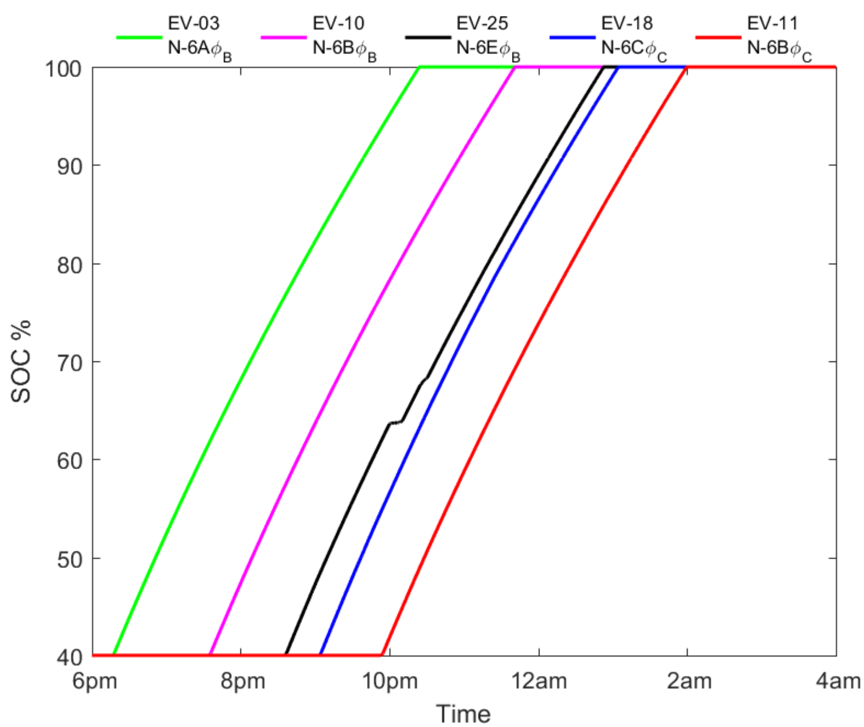

Figure 5-28 SOC of EVs at sub-nodes of Node 6 with Proposed Controller under Heavy Loading Condition

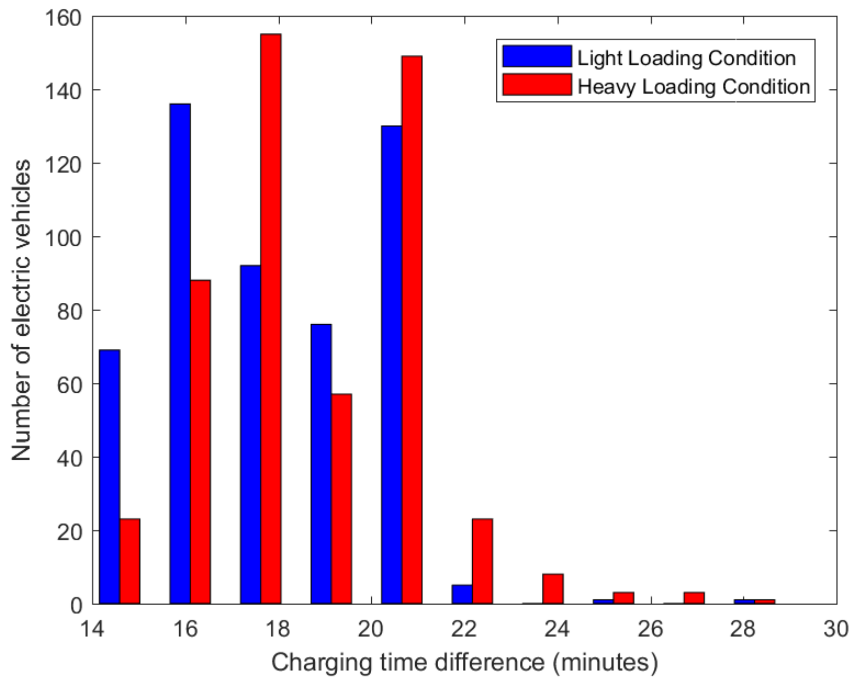

Figure 5-29 Histogram of Charging Time Difference for Proposed and Voltage Feedback Controllers

Table 5.3 Charging Time of EVs with Proposed Control Charging

Loading Condition	Min. Charging Time	Max. Charging Time	Average Charging Time	Std. of Charging Time
Light	3.539 hrs.	3.714 hrs.	3.684 hrs.	0.0210 hrs.
Heavy	3.528 hrs.	4.561 hrs.	3.718 hrs.	0.1028 hrs.

5.5.1 System Reconfiguration Impact

To further evaluate the effectiveness of the proposed controller system topology has been reconfigured, i.e., the Node-4 of system has been eliminated. Even after reconfiguring the system topology, the controller still ensures the fairness among the EVs which can be observed from Table 5.4. The average charging time has been slightly reduced due to decrease in overall system load.

Table 5.4 Charging Time of EVs with Proposed Control Charging after removing Node-4

Loading Condition	Min. Charging Time	Max. Charging Time	Average Charging Time	Std. of Charging Time
Light	3.539 hrs.	3.714 hrs.	3.683 hrs.	0.0214 hrs.
Heavy	3.514 hrs.	4.492 hrs.	3.714 hrs.	0.0951 hrs.

5.5.2 Inclusion of Shunt Capacitors

Shunt capacitor (SC) is installed at Node-5A to evaluate the performance of the proposed controller with voltage support devices. The maximum limit of reactive power that it can provide is set to 1 MVar. It can be seen from Table 5.5 that the proposed controller works effectively with the inclusion of SC into the system. It can also be observed that the average time is further decreased in heavy loading condition. Meanwhile, the controller is ensuring fairness among the EVs irrespective of their charging locations.

Table 5.5 Charging Time of EVs with Proposed Control Charging with SC at Node-5

Loading Condition	Min. Charging Time	Max. Charging Time	Average Charging Time	Std. of Charging Time
Light	3.539 hrs.	3.717 hrs.	3.683 hrs.	0.0218 hrs.
Heavy	3.517 hrs.	4.461 hrs.	3.710 hrs.	0.0855 hrs.

5.5.3 Inclusion of Online-Tap Changing (OLTC) Transformer

The proposed controller is also tested with the inclusion of OLTC transformer at Node-5. The average minimum and maximum voltage limits are set to be 0.985 p.u. and 1.03 p.u. The average voltage profile of Node-5A remains within the limits as shown in Figure 5.30. The minimum, nominal, and maximum tap positions are assumed to be 0, 7, and 14 respectively. The tap position of OLTC transformer at Node-5A is shown in Figure 5.31.

Although the tap changing operation does not seem realistic since it cannot be changed so fast in reality. However, for the sake of simulations it might be considered acceptable. It is evident from Table 5.6 that the proposed controller performs efficiently with the addition of OLTC transformer into the system.

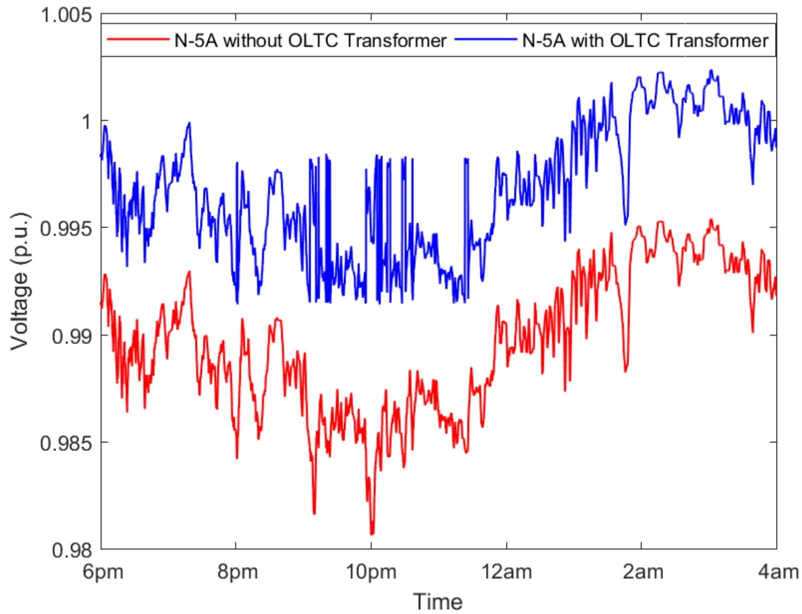

Figure 5-30 Average Voltage Profile of Node-5A with/without OLTC Transformer under Heavy Loading Condition

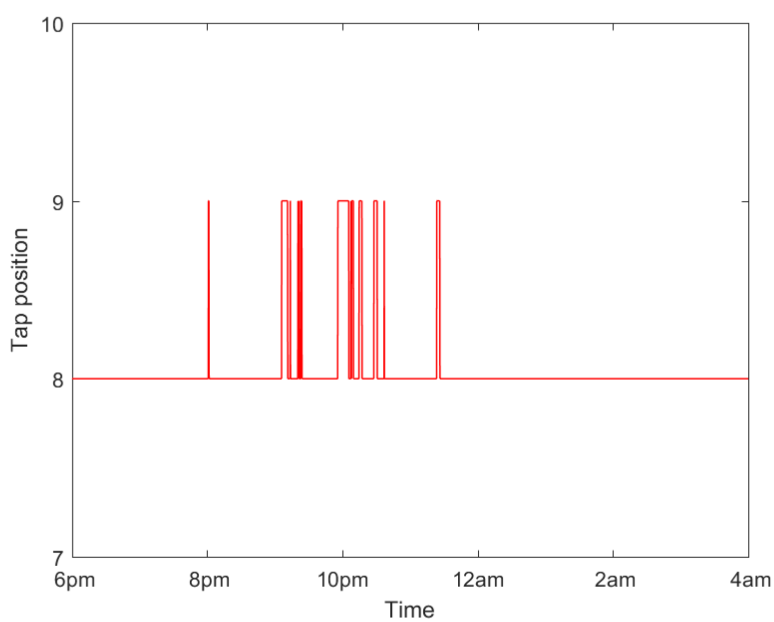

Figure 5-31 Tap Position of OLTC Transformer at Node-5A under Heavy Loading Condition

Table 5.6 Charging Time of EVs with Proposed Control Charging with OLTC Transformer at Node-5

Loading Condition	Min. Charging Time	Max. Charging Time	Average Charging Time	Std. of Charging Time
Light	3.539 hrs.	3.714 hrs.	3.683 hrs.	0.0212 hrs.
Heavy	3.528 hrs.	4.556 hrs.	3.715 hrs.	0.0953 hrs.

5.5.4 Inclusion of Distributed Generator (DG)

DG units have been becoming commonly installed in the secondary distribution system, so, it is extremely important to test the proposed controller when DG unit is added into the system. A wind generator is assumed to be installed at Node-6E. The scaled real power data of wind generator is obtained from Bonneville Power Administration [82] which is shown in Figure 5.32. The rated capacity of DG is assumed to be 4 kW. The minimum, maximum, and average charging times and standard deviation of charging time are provided in Table 5.7. It can be noticed that the proposed controller ensures almost complete fairness among the EVs irrespective of their charging locations. Hence, an efficacy of proposed controller is validated.

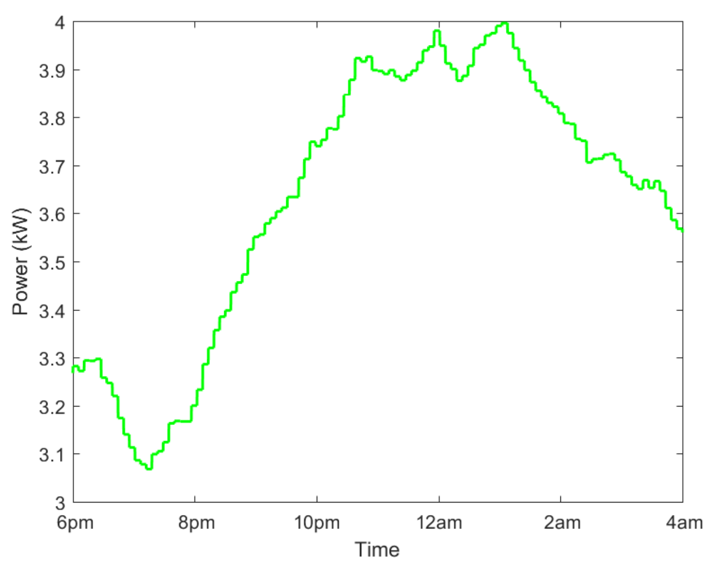

Figure 5-32 Wind Power Variations

Table 5.7 Charging Time of EVs with Proposed Control Charging with DG Unit at Node-6E

Loading Condition	Min. Charging Time	Max. Charging Time	Average Charging Time	Std. of Charging Time
Light	3.539 hrs.	3.714 hrs.	3.684 hrs.	0.0211 hrs.
Heavy	3.528 hrs.	4.561 hrs.	3.717 hrs.	0.1021 hrs.

5.5.5 Inclusion of Tesla Model S

The similar control structure is extended to Tesla Model S to assess the efficacy of the proposed controller. It is assumed that all the houses at Node-4 own Tesla while rest of the houses have Nissan Leaf. The SOCs of EVs (i.e., Tesla) at Node-4 under different loading conditions are shown in Figures 5.33 and 5.34. It can be observed from Table 5.8 that both EV types, i.e., Nissan Leaf and Tesla are charging in a fair pattern which shows that the proposed control architecture can easily be extended to other EV types.

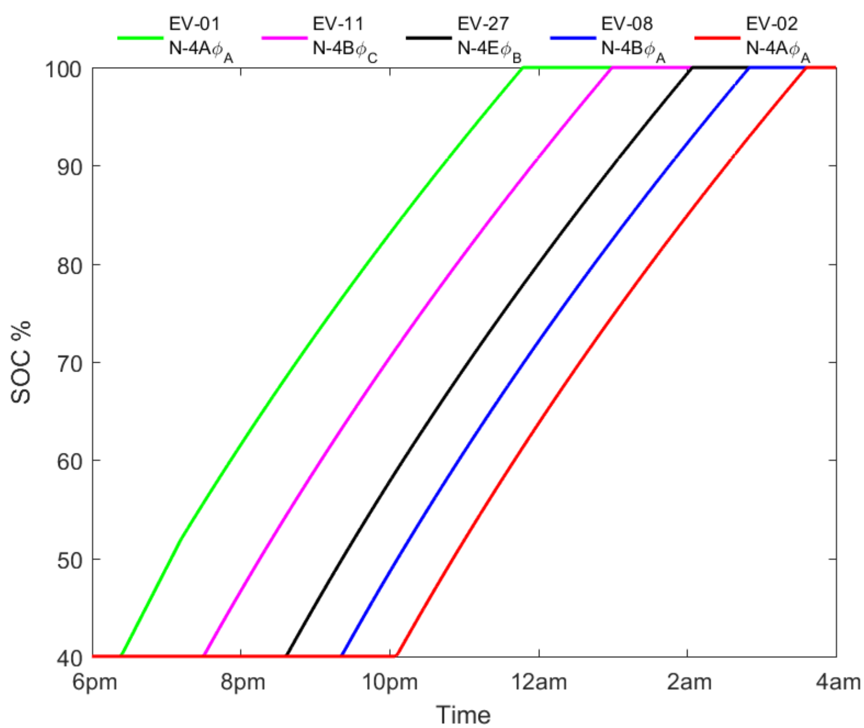

Figure 5-33 SOCs of Tesla EVs at Node-4 under Light Loading Condition

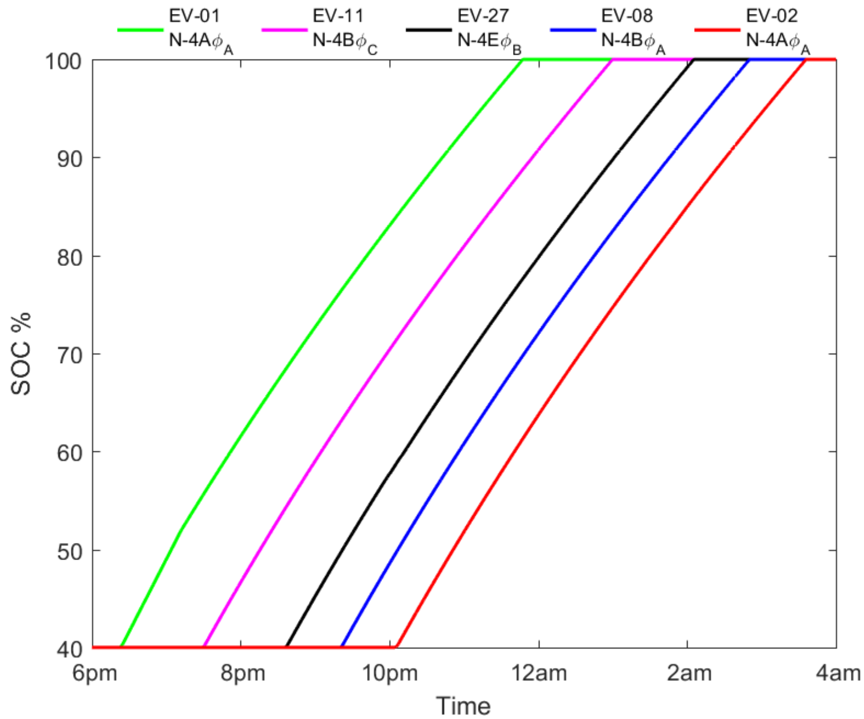

Figure 5-34 SOCs of Tesla EVs at Node-4 under Heavy Loading Condition

Table 5.8 Charging Time of Different EV Types with Proposed Control Charging Structure

EV Type	Loading Condition	Min. Charging Time	Max. Charging Time	Average Charging Time	Std. of Charging Time
Nissan	Light	3.539 hrs.	3.714 hrs.	3.684 hrs.	0.0211 hrs.
Nissan	Heavy	3.531 hrs.	4.575 hrs.	3.719 hrs.	0.1058 hrs.
Tesla	Light	4.881 hrs.	5.038 hrs.	4.951 hrs.	0.0311 hrs.
Tesla	Heavy	4.881 hrs.	5.400 hrs.	5.033 hrs.	0.1397 hrs.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Conclusion

In this thesis, a novel idea of online measuring sensitivity of voltage to load changes is introduced to implement an autonomous communication-free electric vehicle (EV) charge controller. The voltage and sensitivity are considered as input signals while the charging rate is an output of EV charge controller. The state-of-charge (SOC) of EV battery is also included in the charging control structure which helps to prolong the EV battery life span. The EV charge controller is employed in test distribution system which is built and simulated in DIgSILENT PowerFactory environment. The performance of the proposed EV charge controller is evaluated under light and heavy loading conditions to model the daily, weekly, monthly, and seasonal variations. The performance of the proposed controller is compared with the proportional voltage and adaptive voltage feedback controllers. The proportional controller effectively avoids the voltage violations but does not ensure fairness among the EVs available at upstream and downstream nodes. The fairness issue has been solved in adaptive voltage feedback controller but it is not fully utilizing the system capacity since it is unjustifiably limiting the charging rates. However, the proposed charge controller ensures the fairness among the EVs as well as squeezes the system to higher capacity while avoiding voltage violations. Moreover, it also performs well when system topology is reconfigured which proves the efficacy of the proposed controller. The robustness of controller is further tested by integrating distributed generators (DGs), shunt capacitors (SC), and online-tap changing (OLTC) transformers into the test distribution system. Simulation results prove the effectiveness of the proposed approach and substantiate the fact that the nodes having strong voltage profiles are less voltage-sensitive to change in load, and vice versa. In fact, these complementary characteristics play a significant role in ensuring the fairness among the EVs available at upstream, midstream, and downstream nodes. Hence, the proposed controller structure charges all the EVs almost at the same rate irrespective of their charging locations in the power system. Furthermore, the proposed control structure is implemented for Tesla Model S and results show that it can be extended to other EV types as well.

6.2 Future Work

In future, the proposed EV charge controller can be tested under R/X variations. Moreover, hardware implementation of the controller can be considered. Currently, the charge controller is assumed unidirectional, however, it can be made bidirectional so that vehicle-to-grid process can be incorporated into the proposed control structure. Most importantly, the sensitivity concept can be extended for DG applications.

References

[1] B. Bilgin, P. Magne, P. Malysz, Y. Yang, V. Pantelic, M. Preindl, A. Korobkine, W. Jiang, M. Lawford, and A. Emadi, “Making the case for electrified transportation,” *IEEE Trans. Transport. Electrific.*, vol. 1, no. 1, pp. 4-17, Jun. 2015.

[2] J. de Santiago et al., "Electrical Motor Drivelines in Commercial All-Electric Vehicles: A Review," *IEEE Transactions on Vehicular Technology*, vol. 61, no. 2, pp. 475-484, Feb. 2012.

[3] C. Sulzberger, “An early road warrior: Electric vehicles in the early years of the automobile,” *IEEE Power Energy Mag.*, vol. 2, no. 3, pp. 66–71, May/Jun. 2004.

[4] L. Situ, “Electric vehicle development: The past, present and future,” in *Proc. 3rd Int. Conf. PESA*, 2009, pp. 1–3.

[5] E. Hesla, “Electric propulsion [history],” *IEEE Ind. Appl. Mag.*, vol. 15, no. 4, pp. 10–13, Jul./Aug. 2009.

[6] K. Rajashekara, “History of electric vehicles in General Motors,” in *Conf. Rec. IEEE IAS Annu. Meeting*, 1993, vol. 1, pp. 447–454.

[7] Eur. Commission, White Paper: Roadmap to a Single European Transport Area—Towards a Competitive and Resource Efficient Transport System, Brussels, Belgium, Mar. 28, 2011.

[8] I. IEA, “Global EB outlook,” International Energy Agency, 2013.

[9] X. Wang, Y. Pi, and A. Tang, “Scheduling of electric vehicle charging via multi-server fair queueing”, *IEEE Transactions on parallel and distributed systems*, vol. 28, no. 11, Nov. 2017.

[10] J. A. P. Lopes, F. J. Soares, and P. M. R. Almeida, “Integration of electric vehicles in the electric power system,” *Proc. IEEE*, vol. 99, no. 1, pp. 168–183, Jan. 2011.

[11] L. Pieltain Fernandez, T. Gomez San Roman, R. Cossent, C. Mateo Domingo, and P. Frias, “Assessment of the impact of plug-in electric vehicles on distribution networks,” *IEEE Trans. Power Syst.*, vol. 26, no. 1, pp. 206–213, Feb. 2011.

[12] E. Sortomme, M. Hindi, S. D. J. MacPherson, and S. S. Venkata, “Coordinated charging of plug-in hybrid electric vehicles to minimize distribution system losses,” *IEEE Trans. Smart Grid*, vol. 2, no. 1, pp. 198–206, Mar. 2011.

[13] *IEEE Guide for Loading Mineral-Oil-Immersed Power Transformers Up to and Including 100 mVA with 55 Degrees C or 65 Degrees C Average Winding Rise*, ANSI/IEEE Standard C57.92–1981.

[14] T. A. Short, *Electric Power Distribution Handbook*. Boca Raton, FL, USA: CRC Press, 2004.

[15] "CO_2 emissions from fuel combustion highlights 2016," International Energy Agency (IEA) [Online]. Available: https://www.iea.org/publications/freepublications/publication/CO2EmissionsfromFuelCombustion_Highlights_2016.pdf

[16] R. Hoog, "Life beyond Euro VI," *Automot. Megatrends Mag.*, vol. Q2, pp. 66–67, 2014. [Online]. Available: https://issuu.com/megatrends/docs/automotive_megatrends_magazine_q2_2

[17] U.S. Environmental Protection Agency (EPA). Regulations and Standards: Light-Duty [Online]. Available: http://www.epa.gov/, accessed on Jan. 12, 2015.

[18] C. M. Martinez, X. Hu, D. Cao, E. Velenis, B. Gao and M. Wellers, "Energy management in plug-in hybrid electric vehicles: Recent progress and a connected vehicles perspective," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 6, pp. 4534-4549, June 2017.

[19] "Electric vehicle market penetration in Switzerland by 2020," Alpiq InTec AG, Zürich, Switzerland, 2017.

[20] P. J. Balducci, "Plug-in hybrid electric vehicle market penetration scenarios," Pacific Northwest Nat. Laboratory, Richland, WA, USA, Tech. Note JRC 58748, 2008.

[21] F. Bierau, P. Perlo, B. Müller, A. A. Gomez, T. Coosemans and G. Meyer, "Opportunities for European SMEs in global electric vehicle supply chains in Europe and beyond," *Advanced Microsystems for Automotive Applications*, Springer, Cham, 2016, pp. 223-235.

[22] S. Shafiq, A. T. Al-Awami, "Reliability and economic assessment of renewable microgrid with V2G electric vehicles coordination," *IEEE Jordon. Conf. App. Elec. Eng. And Comp. Tech*, 2015, pp. 1-6.

[23] S. W. Hadley and A. A. Tsvetkova, "Potential impacts of plug-in-hybrid electric vehicles on regional power generation," *Electr. J.*, vol. 22, no. 10, pp. 56-68, 2009.

[24] M. Moeini-Aghtaie, A. Abbaspour, M. Fotuhi-Firuzabad and P. Dehghanian, "PHEVs centralized/decentralized charging control mechanisms: Requirements

and impacts," *2013 North American Power Symposium (NAPS)*, Manhattan, KS, 2013, pp. 1-6.

[25] K. Kaur, R. Rana, N. Kumar, M. Singh and S. Mishra, "A colored petri net based frequency support scheme using fleet of electric vehicles in smart grid environment," *IEEE Transactions on Power Systems*, vol. 31, no. 6, pp. 4638-4649, Nov. 2016.

[26] J. Pillai and B. Bak-Jensen, "Integration of vehicle-to-grid in the Western Danish power system," *IEEE Trans. Sustain. Energy*, vol. 2, no. 1, pp. 12–19, Jan. 2011.

[27] B. Yagcitekin and M. Uzunoglu, "A double-layer smart charging strategy of electric vehicles taking routing and charge scheduling into account," *Applied Energy*, vol. 167, pp. 407-419, April 2016.

[28] D. Steen, L. A. Tuan, O. Carlson and L. Bertling, "Assessment of electric vehicle charging scenarios based on demographical data," *IEEE Transactions on Smart Grid*, vol. 3, no. 3, pp. 1457-1468, Sept. 2012.

[29] Q. Kang, J. Wang, M. Zhou and A. C. Ammari, "Centralized charging strategy and scheduling algorithm for electric vehicles under a battery swapping scenario," *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 3, pp. 659-669, March 2016.

[30] W. Zou, B. Wu, and Z. Liu, "Centralized charging strategies of plug-in hybrid electric vehicles under electricity markets based on spot pricing," *Autom. Elect. Power Syst.*, vol. 35, no. 14, pp. 62–67, 2011.

[31] J. Quirós-Tortós, L. F. Ochoa, S. W. Alnaser and T. Butler, "Control of EV charging points for thermal and voltage management of LV networks," *IEEE Transactions on Power Systems*, vol. 31, no. 4, pp. 3028-3039, July 2016.

[32] M. Ansari, A. T. Al-Awami, E. Sortomme and M. A. Abido, "Coordinated bidding of ancillary services for vehicle-to-grid using fuzzy optimization," *IEEE Transactions on Smart Grid*, vol. 6, no. 1, pp. 261-270, Jan. 2015.

[33] J. deHoog, T. Alpcan, M. Brazil, D. A. Thomas, and I. Mareels, "Optimal charging of electric vehicles taking distribution network constraints into account," *IEEE Trans. Power Syst.*, vol. 30, no. 1, pp. 365–375, Jan. 2014.

[34] J. Hu, S. You, M. Lind, and J. Østergaard, "Coordinated charging of electric vehicles for congestion prevention in the distribution grid," *IEEE Trans. Smart Grid*, vol. 5, no. 2, pp. 703–711, Mar. 2014.

[35] M. A. S. Masoum, P. S. Moses, and S. Hajforoosh, "Distribution transformer stress in smart grid with coordinated charging of plug-in electric vehicles," in *Proc. ISGT*, 2012, pp. 1–8

[36] Z. Peng, Q. Kejun, Z. Chengke, B. G. Stewart, and D. M. Hepburn, "A methodology for optimization of power systems demand due to electric vehicle charging load," *IEEE Trans. Power Syst.*, vol. 27, no. 3, pp. 1628–1636, Aug. 2012.

[37] K. Qian, C. Zhou, and Y. Yuan, "Impacts of high penetration level of fully electric vehicles charging loads on the thermal ageing of power transformers", *Elect. Power Energy Syst.*, vol. 65, pp. 102-112, Feb. 2015.

[38] D. Wu, D. C. Aliprantis and L. Ying, "Load scheduling and dispatch for aggregators of plug-In electric vehicles," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 368-376, March 2012.

[39] P. You, Z. Yang, M. Y. Chow and Y. Sun, "Optimal cooperative charging strategy for a smart charging station of electric vehicles," *IEEE Transactions on Power Systems*, vol. 31, no. 4, pp. 2946-2956, July 2016.

[40] F. J. Soares, P. M. R. Almeinda and J. A. P. Lopes, "Quasi-real-time management of electric vehicles charging", *Elect. Power Syst. Res.*, vol. 108, pp. 293-303, Mar. 2014.

[41] A. D. Giorgio, F. Liberati, and S. Canale, "Electric vehicles charging control in a smart grid: A model predictive control approach," *Control Eng. Practice*, vol. 22, pp. 147-162, 2014.

[42] S. F. Gamal, A. T. Al-Awami, and M. A. Abido, "Fuzzy optimization for the operation of electric vehicle parking lots," *Elect. Power Syst. Res.*, vol. 145, pp. 166–174, Apr. 2017.

[43] J. Van Roy, N. Leemput, F. Geth, R. Salenbien, J. Büscher and J. Driesen, "Apartment building electricity system impact of operational electric vehicle charging strategies," *IEEE Transactions on Sustainable Energy*, vol. 5, no. 1, pp. 264-272, Jan. 2014.

[44] A. Schuller, B. Dietz, C. M. Flath and C. Weinhardt, "Charging strategies for battery electric vehicles: economic benchmark and V2G potential," *IEEE Transactions on Power Systems*, vol. 29, no. 5, pp. 2014-2022, Sept. 2014.

[45] W. Su, M.-Y. Chow, "Computational intelligence-based energy management for a large-scale PHEV/PEV enabled municipal parking deck," *Appl. Energy*, vol. 96, pp. 171-182, August 2012.

[46] Z. Ma, D. S. Callaway, and I. A. Hiskens, "Decentralized charging control of large populations of plug-in electric vehicles," *IEEE Trans. Control Syst. Technol.*, vol. 21, no. 1, pp. 67–78, Jan. 2013.

[47] N. Chen, C. W. Tan and T. Q. S. Quek, "Electric vehicle charging in smart grid: Optimality and valley-filling algorithms," *IEEE Journal of Selected Topics in Signal Processing*, vol. 8, no. 6, pp. 1073-1083, Dec. 2014.

[48] W. Qi, Z. Xu, Z. J. M. Shen, Z. Hu and Y. Song, "Hierarchical coordinated control of plug-in electric vehicles charging in multifamily dwellings," *IEEE Transactions on Smart Grid*, vol. 5, no. 3, pp. 1465-1474, May 2014.

[49] L. Gan, U. Topcu and S. H. Low, "Optimal decentralized protocol for electric vehicle charging," *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 940-951, May 2013.

[50] G. Binetti, A. Davoudi, D. Naso, B. Turchiano and F. L. Lewis, "Scalable real-time electric vehicles charging with discrete charging rates," *IEEE Transactions on Smart Grid*, vol. 6, no. 5, pp. 2211-2220, Sept. 2015.

[51] M. Liu, P. K. Phanivong, Y. Shi and D. S. Callaway, "Decentralized charging control of electric vehicles in residential distribution networks," *IEEE Transactions on Control Systems Technology*, vol. PP, no. 99, pp. 1-16, 2017.

[52] J. H. Teng, S. H. Liao and C. K. Wen, "Design of a fully decentralized controlled electric vehicle charger for mitigating charging impact on power grids," *IEEE Transactions on Industry Applications*, vol. 53, no. 2, pp. 1497-1505, March-April 2017.

[53] A. Ghavami, K. Kar and A. Gupta, "Decentralized charging of plug-in electric vehicles with distribution feeder overload control," *IEEE Transactions on Automatic Control*, vol. 61, no. 11, pp. 3527-3532, Nov. 2016.

[54] C. K. Wen, J. C. Chen, J. H. Teng and P. Ting, "Decentralized plug-in electric vehicle charging selection algorithm in power systems," *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 1779-1789, Dec. 2012.

[55] R. Wang, G. Xiao and P. Wang, "Hybrid centralized-decentralized (HCD) charging control of electric vehicles," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 8, pp. 6728-6741, Aug. 2017.

[56] N. Leemput, F. Geth, J. Van Roy, A. Delnooz, J. Büscher and J. Driesen, "Impact of electric vehicle on-board single-phase charging strategies on a Flemish

residential grid," *IEEE Transactions on Smart Grid*, vol. 5, no. 4, pp. 1815-1822, July 2014.

[57] F. Geth, N. Leemput, J. Van Roy, J. Büscher, R. Ponnette, and J. Driesen, "Voltage droop charging of electric vehicles in a residential distribution feeder," in *Proc. IEEE Power Energy Soc. Innovative Smart Grid Technol. Conf. Eur.*, Berlin, Germany, 2012, pp. 1–8.

[58] S. Huang, J. R. Pillai, and P. Thøgersen, "Voltage support from electric vehicles in distribution grid," in *Proc. 15th Eur. Conf. Power Electron. Applicat.*, Lille, France, 2013, pp. 1–8.

[59] Y. Ota, H. Taniguchi, J. Baba, and A. Yokoyama, "Implementation of autonomous distributed V2G to electric vehicle and DC charging system," *Electric Power Systems Research*, vol. 120, pp. 177-183, Mar. 2015.

[60] Y. Ota, H. Taniguchi, T. Nakajima, K. M. Liyanage, J. Baba, and A. Yokoyama, "Autonomous distributed V2G (vehicle-to-grid) satisfying scheduled charging," *IEEE Trans. Smart Grid*, vol. 3, no. 1, pp. 559– 564, Mar. 2012.

[61] H. Turker, A. Hably, S. Bacha, and D. Chatroux, "Rule based algorithm for plug-in hybrid electric vehicles (PHEVs) integration in residential electric grid areas," *2012 IEEE PES Innovative Smart Grid Technologies (ISGT),* 2012, pp. 1–7.

[62] S. Faddel, A. A. S. Mohamed, and O. A. Mohammed, "Fuzzy logic based autonomous controller for electric vehicles charging under different conditions in residential distribution systems," *Elect. Power Syst. Res.*, vol. 148, pp. 48–58, Jul. 2017.

[63] P. Richardson, D. Flynn, and A. Keane, "Local versus centralized charging strategies for electric vehicles in low voltage distribution systems," *IEEE Trans. Smart Grid*, vol. 3, no. 2, pp. 1020–1028, Jun. 2012.

[64] A. T. Al-Awami and E. Sortomme, "Electric vehicle charging modulation using voltage feedback control," in *2013 IEEE Power & Energy Society General Meeting*, 2013.

[65] G. M. A. Akhtar, A. T. Al-Awami, E. Sortomme, M. A. Abido and M. W. Ahmed, "Autonomous electric vehicle charging management over real time digital simulator," *2014 IEEE PES General Meeting | Conference & Exposition*, National Harbor, MD, 2014, pp. 1-5.

[66] S. Faddel, A. T. Al-Awami and M. A. Abido, “Real time digital simulation of voltage-based controller for electric vehicle charging,” *2016 Clemson University Power Systems Conference (PSC)*, Clemson, SC, 2016, pp. 1-5.

[67] A. T. Al-Awami, E. Sortomme, G. M. A. Akhtar and S. Faddel, “A voltage-based controller for an electric-vehicle charger,” *IEEE Transactions on Vehicular Technology*, vol. 65, no. 6, pp. 4185-4196, June 2016.

[68] G. Valverde and T. V. Custsem, “Model predictive control of voltages in active distribution networks,” *IEEE Trans. Smart Grid*, pp. 2152-2161, Feb. 2013.

[69] Q. Zhou and J. Bialek, “Simplified calculation of voltage and loss sensitivity factors in distribution networks,” in *Proc. 16th Power Syst. Compute. Conf. (PSCC)*, Glasgow, U.K., 2008.

[70] T. Sansawatt, L. F. Ochoa, “Smart decentralized control of DG for voltage and thermal constraint management,” *IEEE Trans. Power Syst.*, vol. 27, no. 3, pp. 1637-1645, Aug. 2012.

[71] P. Richardson, D. Flynn and A. Keane, “Optimal charging of electric vehicles in low-voltage distribution systems,” *IEEE Transactions on Power Systems*, vol. 27, no. 1, pp. 268-279, Feb. 2012.

[72] X. Luo and K. W. Chan, “Real-time scheduling of electric vehicles charging in low-voltage residential distribution systems to minimise power losses and improve voltage profile,” *IET Generation, Transmission & Distribution*, vol. 8, no. 3, pp. 516-529, March 2014.

[73] Z. Zhang, L. F. Ochoa and G. Valverde, “A novel voltage sensitivity approach for the decentralized control of DG plants,” *IEEE Transactions on Power Systems*, vol. PP, no. 99, pp. 1-1, 2017.

[74] C. Murphy and A. Keane, “Optimised voltage control for distributed generation,” *PowerTech, 2015 IEEE Eindhoven*, Jul. 2015.

[75] S. Weckx, R. D‟Hulst, J. Driesen, “Voltage sensitivity analysis of a laboratory distribution grid with incomplete data,” *IEEE Trans. Smart Grid*, vol. 6, no. 3, pp. 1271-1280, Apr. 2015.

[76] J. Van Roy, N. Leemput, S. De Breucker, F. Geth, P. Tant, and J. Driesen, “An availability analysis and energy consumption model for a flemish fleet of electric vehicles,” in *Proc. Eur. Electric Veh. Congr.*, Brussels, Belgium, 2011, pp. 1–12.

[77] *American National Standard for Electrical Power Systems and Equipment—Voltage Ratings (60 Hertz)*, ANSI Std. C84.1-2006.

[78] IEC TC69, “IS 61851-1:2010 Ed. 2.0,” *IEC Standard*, 2010.

[79] “Nissan electric cars website, Leaf specs,” 2016 [Online]. Available: https://www.nissanusa.com/electric-cars/leaf/versions-specs/

[80] “Tesla model S specs,” Tesla Motors, 2016 [Online]. Available: https://www.tesla.com/models

[81] DIgSILENT, DIgSILENT technical documentation, DIgSILENT GmbH, 2016.

[82] Bonneville Power Administration (BPA), “Wind Data,” [Accessed: July, 2017]. [Online]. Available: https://transmission.bpa.gov/business/operations/wind /baltwg.aspx

Vitae

Name:	Saifullah Shafiq
Nationality:	Pakistani
Date of Birth:	11/28/1991
Email:	saifullah_shafiq10@yahoo.com
Address:	H. No. 28 B-1, Street No. 82, New Muslim Colony, Rajgarh, Lahore, 54000, Pakistan
Academic Background:	M. Sc. Electrical Engineering, King Fahd University of Petroleum & Minerals, Dhahran, Saudi Arabia, Dec. 2017. B. Sc. Electrical Engineering, University of Engineering and Technology (UET), Lahore, Pakistan, August 2014.
List of Publications:	S. Shafiq and A. T. Al-Awami, “A Novel Communication-Free Charge Controller for Electric Vehicles,” submitted to IEEE Industry Applications Society (IAS) Annual Meeting, 2018.